University of Alberta

AUTOMATION OF WATER TREATMENT PLANTS WITH ARTIFICIAL NEURAL NETWORKS AND REMOTE MONITORING SYSTEMS

by

Riyaz Shariff ©

A thesis submitted to the Faculty of Graduate Studies and Research in partial fulfillment
of the requirement for the degree of **Master of Science**

in

Environmental Engineering

Department of Civil and Environmental Engineering

Edmonton, Alberta
Fall 2002

National Library
of Canada

Acquisitions and
Bibliographic Services

395 Wellington Street
Ottawa ON K1A 0N4
Canada

Bibliothèque nationale
du Canada

Acquisitions et
services bibliographiques

395, rue Wellington
Ottawa ON K1A 0N4
Canada

Your file Votre référence

Our file Notre référence

The author has granted a non-exclusive licence allowing the National Library of Canada to reproduce, loan, distribute or sell copies of this thesis in microform, paper or electronic formats.

The author retains ownership of the copyright in this thesis. Neither the thesis nor substantial extracts from it may be printed or otherwise reproduced without the author's permission.

L'auteur a accordé une licence non exclusive permettant à la Bibliothèque nationale du Canada de reproduire, prêter, distribuer ou vendre des copies de cette thèse sous la forme de microfiche/film, de reproduction sur papier ou sur format électronique.

L'auteur conserve la propriété du droit d'auteur qui protège cette thèse. Ni la thèse ni des extraits substantiels de celle-ci ne doivent être imprimés ou autrement reproduits sans son autorisation.

0-612-81474-2

Canada

University of Alberta

Library Release Form

Name of Author:	Riyaz Shariff
Title of Thesis:	Automation of Water Treatment Plants with Artificial Neural Networks and Remote Monitoring Systems
Degree:	Master of Science
Year this Degree Granted:	2002

Permission is hereby granted to the University of Alberta Library to reproduce single copies of this thesis and to lend or sell such copies for private, scholarly, or scientific research purposes only.

The author reserves all other publication and other rights in association with the copyright in the thesis, and except as hereinbefore provided, neither the thesis nor any substantial portion thereof may be printed or otherwise reproduce in any material form whatever without the author's prior written permission.

Riyaz Shariff
1205, 8210 – 111 Street
Edmonton, Alberta
T6G 2C7

Date: 26-Sep-2002

University of Alberta

Faculty of Graduate Studies and Research

The undersigned certify that they have read, and recommend to the Faculty of Graduate Studies and Research for acceptance, a thesis entitled **Automation of Water Treatment Plants with Artificial Neural Networks and Remote Monitoring Systems** submitted by **Riyaz Shariff** in partial fulfillment of the requirements for the degree **of Master of Science** in Environmental Engineering.

Dr. S.J. Stanley

David W. Smith
Dr. D.W. Smith

Ian Buchanan
Dr. I.D. Buchanan

Dr. S.E. Hrudey

Date: 6-Sep-2002

Abstract

Water utilities faced with making improvements to the operation of their plants due to stringent water quality standards, rising costs, limited revenues, and public scrutiny on the aesthetics and safety of water are considering automating their plants. This thesis is concerned with developing practical automation systems using artificial neural network models (ANN's), advanced controls, and remote monitoring techniques.

The research developed ANN models for Edmonton's Rossdale water plant softening clarifier with an average accuracy of 1% of actual performance. Practical ANN applications developed included: softening cost estimation, inferential sensors, and real-time advanced control of clarifiers.

For successful remote operation of smaller simpler plants, it was determined that reliable on-line analyzers, remote communication, and SCADA systems are required. When implementing remote operations for E.L. Smith (a larger more complex plant) both automation as well as people issues required addressing. Finally, a pilot study evaluation of five chlorine analyzers is also presented.

Acknowledgements

I would first like to thank my supervisor, Dr. Stephen J. Stanley, for his sound guidance, practical approach in directing my thesis and his enthusiastic and unwavering support for this area of work. I also thank Dr. Daniel W. Smith, my co-supervisor for all his assistance and support.

I would also like to sincerely thank Audrey Cudrak and David Rector: Audrey for taking the time to review the draft thesis and providing invaluable suggestions to make it better; and David for inspiring and convincing me to pursue this area of research in the first place. I thank you both for your continual encouragement and in helping me view the work involved as achievable.

I also acknowledge Simon Thomas and Mark Penney for their contribution to this thesis; the operations staff at Edmonton's two water treatment plants and in particular, the plant and distribution shift operators who have been very supportive to me not only in this work but throughout my career with EPCOR Water Services. I would like to thank Steve Hrudey Jr., Tina Mendes and Fatima Kassamali for their contributions during their co-op engineering work term with EPCOR Water Services.

I would like to also acknowledge Qing Zhang for introducing me to the world of artificial neural network modeling and model-based control techniques.

Lastly, I would like to express my sincere appreciation to EPCOR Water Services for supporting this research work and allowing me to test and implement state-of-the-art designs at the water plants.

Dedication

To my parents and siblings – for your unconditional support and concern for my well being.

Table of Contents

1.0 INTRODUCTION 1

1.1 Thesis Organization *1*

1.2 Background *1*

1.3 Objectives *4*

1.4 References *6*

2.0 LIME SOFTENING CLARIFIER MODELING WITH ARTIFICIAL NEURAL NETWORKS 7

2.1 Introduction *7*

2.1.1 Modeling of Processes 9

2.1.2 Project History and Scope 11

2.2 Overview of the Rossdale Water Treatment Plant *12*

2.2.1 Raw Water Quality and Chemical Dosage Ranges 12

2.2.2 Treatment Process Units 14

2.2.3 Softening Clarifier Process Control 18

2.3 Lime Softening *20*

2.3.1 Classification of Hardness 21

2.3.2 Chemistry of Softening 22

2.3.3 Lime Dose Calculations 25

2.4 Artificial Neural Networks *26*

2.4.1 Introduction 26

2.4.2 ANN Model Components 27

2.5 Model Development and Evaluation *30*

2.5.1 Forward and Inverse Models 30

2.5.2 Modeling Protocol 32

2.5.3 Source Data Analysis 33

2.5.4 Model Design 39

2.5.5 Model Evaluation 43

2.6 Discussion and Applicability of ANN Models *52*

2.7 Conclusions ____ *55*

2.8 References ____ *57*

3.0 INTEGRATION OF ARTIFICIAL NEURAL NETWORKS WITH REAL-TIME PROCESS CONTROL SYSTEMS **60**

3.1 Introduction ____ *60*

3.2 Artificial Neural Network Models in Process Control ____ *61*

3.2.1 Conventional Process Control Schemes 61

3.2.2 Advanced Process Control Schemes 63

3.2.3 Inferential Sensing 70

3.2.4 Issues with On-line ANN Execution 74

3.3 ANN Model Integration with Real-time Control Systems ____ *77*

3.3.1 Integration Requirements 77

3.3.2 Lime Softening ANN Model Integration with Control System 84

3.4 Looking to the Future ____ *90*

3.5 Conclusions and Recommendations ____ *92*

3.6 References ____ *94*

4.0 REMOTE MONITORING AND OPERATION OF ISOLATED SMALL WATER FACILITIES IN COLD REGIONS **97**

4.1 Introduction ____ *97*

4.2 Background ____ *97*

4.2.1 On-line Analyzer Systems 100

4.2.2 Remote Communication Systems 103

4.2.3 Supervisory Control and Data Acquisition (SCADA) Systems 104

4.3 Pilot Study ____ *105*

4.3.1 Objectives 105

4.3.2 Pilot Setup 106

4.3.3 Results 110

4.4 Conclusions ____ *114*

4.5 References ____ *116*

5.0 AUTOMATION AND UNATTENDED OPERATION OF THE E.L. SMITH WATER TREATMENT PLANT **118**

5.1 ***Introduction*** ***118***
5.1.1 Scope 119
5.2 ***Overview of the E.L. Smith Water Treatment Plant*** ***119***
5.2.1 Treatment Processes 119
5.2.2 Control Systems 121
5.3 ***Methodology*** ***122***
5.4 ***Implementation*** ***126***
5.4.1 Chemical Feed Systems 127
5.4.2 Electrical, UPS, Power, Fire alarms 128
5.4.3 Filters 128
5.4.4 On-line Analyzers 129
5.4.5 Automatic Shutdown Systems 129
5.4.6 SCADA Systems 129
5.4.7 Security Systems 130
5.4.8 Training 131
5.4.9 Communication 131
5.4.10 Shift Changes 131
5.4.11 Approval to Operate 132
5.4.12 Departure/Security/Alarm Response Procedures 132
5.4.13 Electronic Log Books 133
5.4.14 Pilot Trial 133
5.5 ***Results and Discussion*** ***133***
5.5.1 Other Observations: 134
5.5.2 Post Implementation Review 135
5.6 ***Conclusions*** ***137***
5.7 ***References*** ***138***
6.0 CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE STUDY 139
6.1 ***Conclusions*** ***139***
6.2 ***Recommendations for Future Study*** ***142***
APPENDIX A LIME SOFTENING CLARIFIER MODELING WITH ARTIFICIAL NEURAL NETWORKS 144

APPENDIX B INTEGRATION OF ARTIFICIAL NEURAL NETWORKS WITH REAL-TIME PROCESS CONTROL SYSTEMS 152

APPENDIX C REMOTE MONITORING AND OPERATION OF ISOLATED SMALL WATER FACILITIES IN COLD REGIONS 158

APPENDIX D AUTOMATION AND UNATTENDED OPERATION OF THE E.L. SMITH WATER TREATMENT PLANT 164

List of Tables

TABLE 2-1 Degree of hardness of water (after Sawyer et al, 1994) 7
TABLE 2-2 Raw water quality and chemical dosages at the Rossdale WTP (prior to spring 2000) 13
TABLE 2-3 Typical raw water conditions and production rates for the Rossdale WTP's (prior to 2000) 14
TABLE 2-4 Clarifier volumes and residence times for the Rossdale WTP's. 17
TABLE 2-5 Hardness definitions 21
TABLE 2-6 Measured parameters, accuracy, and sampling frequency 34
TABLE 2-7 Preliminary ANN model design parameters 38
TABLE 2-8 Ward 5-layer BP neural network details 40
TABLE 2-9 Forward modeling trial runs for the overall softening process 42
TABLE 2-10 Inverse modeling trial runs for the overall softening process 42
TABLE 2-11 Forward modeling trial runs for the alum clarifier process (Virtual pH) 43
TABLE 2-12 Inverse modeling trial runs for the alum clarifier process 43
TABLE 2-13 Performance of candidate ANN models 44
TABLE 4-1 Specification of each analyzer as quoted by the manufacturer 107
TABLE 4-2 Additional built-in or optional features of each analyzer 107
TABLE 4-3 Summary of bench versus on-line analyzers 111
TABLE 5-1 Range of raw water quality and chemical dosages at the E.L. Smith WTP 120
TABLE 5-2 Plant systems assessment list 125
TABLE 5-3 Rating of recommendations 127
TABLE A-1 Water quality guidelines for EPCOR plants in Edmonton (1997 version) 145
TABLE A-2 Actual Rossdale WTP plant 2 process data and model results 149
TABLE C-1 Raw data from the on-line chlorine analyzer pilot test (all values are in mg/L free chlorine) (after Penny, 2001) 162
TABLE C-2 Cost analysis of various on-line chlorine analyzers 163

List of Figures

FIGURE 2-1 Trade-off between model reliability and complexity (after Chapra, 1997) 10
FIGURE 2-2 Process schematic for the Rossdale Water Treatment plants (pre 2000) 15
FIGURE 2-3 Effect of pH on the species composition of a carbonic acid system (after Benefield, 1982) 22
FIGURE 2-4 A simple artificial neural network (after Zhang, 1996) 27
FIGURE 2-5 An artificial neuron (after Zhang, 1996) 28
FIGURE 2-6 Data flow in error back-propagation training of ANN (after Boger 1992) 30
FIGURE 2-7 Forward and inverse model architecture for a softening process 31
FIGURE 2-8 Softening clarifier effluent total hardness 36
FIGURE 2-9 Softening clarifier influent lime dose 37
FIGURE 2-10 Ward 5-layer BP neural network architecture (after Ward, 1996) 40
FIGURE 2-11 Alum clarifier effluent pH ANN 45
FIGURE 2-12 Alum clarifier influent alum dose ANN 46
FIGURE 2-13 Softening clarifier effluent total hardness ANN 47
FIGURE 2-14 Softening clarifier influent lime dose ANN 47
FIGURE 2-15 Performance comparison of softening clarifier effluent total hardness predictions using the USEPA WTP model and the ANN models 48
FIGURE 2-16 On-line performance of the softening clarifier ANN models 49
FIGURE 2-17 Residuals plot for the effluent total hardness ANN model 50
FIGURE 2-18 Residuals plot for the lime dose ANN model 51
FIGURE 3-1 Forward and inverse models 64
FIGURE 3-2 Ideal model-based (feed-forward) control scheme for a softening clarifier 66
FIGURE 3-3 Example of an Internal Model Control scheme 68
FIGURE 3-4 Structure of an optimization scheme (after Willis and Tham, 1994) 69
FIGURE 3-5 Overall plant control strategy example 70
FIGURE 3-6 Using a "soft-sensor" as part of a control loop (after Tham, 2000) 72
FIGURE 3-7 Modeling the lime softening clarifier and virtual pH meter (after Stanley et al, 2001) 73
FIGURE 3-8 SCADA system layout for a generic water treatment plant 79
FIGURE 3-9 ANN control system integration information flow 82
FIGURE 3-10 Visual Basic code (partial listing) in Excel of a runtime pH ANN model 86
FIGURE 3-11 Standalone manual ANN interface for pH and lime dose 87
FIGURE 3-12 Real-time information flow path for the softening ANN control 88

FIGURE 3-13 Real-time ANN interface for pH and lime dose 89
FIGURE 4-1 Groundwater source plant using free chlorine 98
FIGURE 4-2 Schematic of chlorine analyzer pilot test 109
FIGURE 4-3 Pilot Study Internet Communication Layout 110
FIGURE 4-4 Three days of historical data from SCADA for the Swan, HACH, and Endress and Hauser free chlorine analyzers 112
FIGURE 5-1 E.L. Smith WTP process flow diagram (2000) 120
FIGURE 5-2 EPCOR Water Services control system layout 122
FIGURE A-1 USEPA WTP modeling software input screen 1 146
FIGURE A-2 USEPA WTP modeling software input screen 2 146
FIGURE A-3 USEPA WTP modeling software input screen 3 147
FIGURE A-4 USEPA WTP modeling software input screen 4 147
FIGURE A-5 USEPA WTP modeling software results screen 148
FIGURE B-1 A Visual Basic off-line user interface for ANN 153
FIGURE B-2 A web-based off-line user interface for ANN 154
FIGURE B-3 Analog input read-back configuration on SCADA database 155
FIGURE B-4 Real-time ANN interface on plant SCADA HMI 156
FIGURE B-5 Lime dose and total hardness actual and ANN predicted values from the SCADA historian 157
FIGURE C-1 Chlorine analyzer pilot test layout at the Rossdale Water Treatment Plant 159
FIGURE C-2 Chlorine analyzer pilot test – chlorine sample recirculation tank 160
FIGURE C-3 Chlorine analyzer pilot test – bench chlorine residual measurement equipment .. 161
FIGURE C-4 Trend of raw data from the on-line chlorine analyzer pilot test 163
FIGURE D-1 Comprehensive SCADA graphic of the E.L. Smith WTP 165
FIGURE D-2a E.L. Smith Remote Operations Newsletter #1 Page 1 of 2 166
FIGURE D-2b E.L. Smith Remote Operations Newsletter #1 Page 2 of 2 167

List of Abbreviations

AEnv	Alberta Environment
ANN	Artificial Neural Network
CWS	Community Water Systems
DDE	Dynamic Data Exchange
DPD	N,N-diethyl-*p*-phenylenediamine sulphate
EWSI	EPCOR Water Services Incorporated
HMI	Human Machine Interface
IMC	Internal Model Control
MCL	Maximum Contaminant Level
MBC	Model-Based Control
meq/L	milliequivalents per litre
mg/L	milligrams per litre
min	minutes
ML	Megalitre
ML/d	Megalitre per day
MPC	Model Predictive Control
NTU	Nephelometric Turbidity Unit
PLC	Programmable Logic Controller
PID	Proportional-Integral-Derivative
R^2	Regression Error Statistic. Used by the NeuroShell2 ANN software. A value of 1 indicates a perfect fit.
RTU	Remote Terminal Unit
SCADA	Supervisory Control and Data Acquisition
TCU	True Colour Units
UPS	Uninterruptible Power Supply
USEPA	United States Environmental Protection Agency
WTP	Water Treatment Plant

1.0 INTRODUCTION

1.1 Thesis Organization

This thesis describes the development and use of automation techniques including advanced process control and remote monitoring systems for improving the operation of drinking water treatment plants. It is organized into six sections.

In the introduction section, a brief discussion on the topic is presented and the specific objectives of the study are identified. In the second section, the development of full-scale artificial neural network (ANN) based models for a lime softening process is presented. The third section begins with a description of advanced model-based control (MBC) techniques and methods for integrating ANN with real-time control systems. The section concludes with an illustration of how the softening models developed earlier were integrated using an MBC scheme with a plant real-time control system.

The fourth section discusses some of the challenges facing small isolated water systems and how the use of on-line instrumentation and remote monitoring equipment can help small systems improve their water quality. The fifth section describes the methodology that was used to convert a large water treatment facility from a 24-hour on-site operation to unattended operation for periods of time. In the final section, conclusions and recommendations from this work are presented.

1.2 Background

Virtually all water utilities are faced with making improvements to the operation of their plants due to increasingly more stringent water quality regulations, rising costs of operation, limited revenues, and public scrutiny on aesthetics and safety of their water. As a result, utilities are beginning to look at automation as a means to manage their plants more efficiently, reliably, and to produce better quality water. Automation entails eliminating intermediate components or steps in a process, especially those involving human intervention or decision-making, and replacing them with technologically more advanced ones of which there are three general categories (Schlenger et al, 1996):

Supervisory Control: Operator directed control using information from laboratory analysis and plant instrumentation. Based on skill level and established procedures, the operator makes operating decisions and manually adjusts control devices to regulate treatment process. It can be implemented with hard-wired instrumentation or with computerized monitoring equipment.

Automatic Control: With appropriate instrumentation and control equipment provided, adjustments are made automatically based on relatively simple operating rules. Typical automatic controls include chemical feed flow pacing, pump start-stop, pressure control, and level control. Operators monitor the process and take action when necessary. Automatic control can be implemented with hard-wired relay logic and panel mounted instruments, or as is more typical in newer systems, with computer control equipment.

Advanced Control: Implies the use of complex and sophisticated optimizers and algorithms, process models, or artificial intelligence methods in making operating decisions. Operators monitor the overall process and take action when required. Advanced control is always implemented with a computerized process control system.

Furthermore, the level of operator staffing can also be generalized in three categories (Schlenger et al, 1996):

Level 3: Fully attended. Water facility is staffed by at least one operator 24 hours per day.

Level 1-2: Partially attended. For at least one shift each day, water is produced without any operators on duty at the facility.

Level 0: Unattended for substantial periods of time. Routine operation of the facility without any operators on duty although utility personnel may make regular visits.

As the degree of control required to reliably operate a plant increases, the level of automation and/or staffing required increases as well. With increased pressures to reduce costs of operation, operator staffing levels are becoming more difficult to increase and may in fact be declining. When coupled with a lack of automation, operating plants reliably becomes even more difficult. Automation can help by improving productivity and to minimize staffing increases. However, for many small water plants (particularly those that are remotely located and isolated), not only is the level of staffing level low (unattended), but so is the level of automation in the plants. As a result, small water plants tend to experience a higher incidence of water quality problems. A study of drinking water quality in Northern Canada (Armstrong et al, 1996) found that small systems in the study region had higher treated water turbidity than larger systems and also had the highest percent of coliform positive samples. It was reported (USEPA, 2001) that 86% of systems in violation of the MCL (Maximum Contaminant Level – the highest level of a contaminant allowed in drinking water set and enforced by the USEPA) are also the ones that serve less than 3,300 people (i.e. small systems). By increasing the level of automation through the use of on-line monitoring equipment and controls, and by providing 24 hour a day monitoring from a central control center, it is thought that improvements to water quality on a consistent basis can be achieved (Shariff et al, 2001).

When a plant's automation level falls in the category of "automatic control", traditional control methods are generally utilized for controlling water and chemical feed flow rates, level, pH, chlorine residuals, pressures, pumping, valve sequencing on filters, and so on. Many plants also have unit processes such as alum clarification to control turbidity and colour (organics), lime softening to reduce hardness, and filtration to remove a large portion of the remaining turbidity. In automating these treatment process units effectively, traditional control methods are generally inadequate due to the characteristics that are inherently present in these processes such as non-linear dynamics, multiple interacting control variables, and large dead (delay) times. Mechanistic models for these processes are also either not available or are less than adequate in describing them. Compounding this is that even if the individual process units could be optimized, it does

L

not always guarantee best overall performance in terms of finished water quality and costs of production.

The use of only conventional controls can therefore be a limiting factor towards realizing higher levels of water quality and efficiency at more sophisticated water plants. This is especially true of plants that are subjected to a wide range in raw water quality and especially if the changes in quality occur rapidly. In other process industries it has been recognized that advanced process control techniques that incorporate models of processes represent the most effective technology available today to meet the challenge of reducing variable costs while maintaining product quality (Willis and Tham, 1994).

Advanced process control schemes are designed to better handle non-linear process dynamics and time-delays. They can be made adaptive or self-correcting and many incorporate models to predict set-points. These are known as model-based control (MBC) schemes. Since accurate models are the cornerstone of every MBC scheme, modeling of water treatment processes becomes a requirement when implementing advanced controls.

A promising technique for developing robust models for water treatment processes is artificial neural networks (ANN). It is gaining popularity and several models have been developed for water treatment processes (Baxter et al, 2001). When coupled with real-time systems, the ANN modeling technique is expected to play an important part in water treatment plant operation, process optimization, plant-wide control and decision making systems.

1.3 Objectives

The overall objective of this thesis is to develop some appropriate automation techniques suitable for drinking water treatment plants to help utilities improve the quality and consistency of water and costs. The techniques developed address a full spectrum of plants from small isolated production facilities that require only basic treatment to larger more sophisticated plants that must deal with difficult treatment challenges and increasing costs of production. To this end, the thesis is focused on two major areas of automation: advanced control techniques and remote monitoring techniques.

The specific objectives of this work are:

1. To model the full-scale lime softening process at EPCOR's Rossdale Water Treatment Plant in Edmonton, Alberta, Canada, using the artificial neural network (ANN) modeling technology. To develop and illustrate the use of inferential sensors.

2. To develop computer process control methods for integrating ANN models into a SCADA (Supervisory Control and Data Acquisition) system. To test in real-time the softening models developed earlier using a model-based feed-forward control scheme.

3. To develop reliable and cost effective automation and remote monitoring methods for small remotely located and isolated water systems. To conduct a pilot study evaluation of on-line chlorine analyzers to identify ones that would be most suitable for these plants. To illustrate that with advances in on-line monitoring equipment, SCADA systems, and communication systems, it is possible to monitor and even operate small water systems remotely and that this can have a significant impact in improving drinking water quality in small communities.

4. To implement unattended operation of a large conventional water treatment facility, namely EPCOR's E.L. Smith Water Treatment Plant in Edmonton, Alberta, Canada. To identify all issues (personnel, process, security, communication, controls, redundancy, etc.) and determine solutions to mitigate the issues within a fixed budget and time frame.

1.4 References

1. Armstrong, T. F., Prince, D. S., Stanley, S. J., Smith, D. W. 1996. Assessment of Drinking Water Quality in the Northern River Basin Study Area Syntheses Report. Northern River Basins Study Report No. 9. Edmonton, Alberta. 153 p.

2. Baxter, C.W., Zhang, Q., Stanley, S. J., Shariff, R., Tupas, R-R, Stark, H. L. 2001. Drinking Water Quality and Treatment: The Use of Artificial Neural Networks. Can. J. Civ. Eng., 28(Suppl. 1):26-35

3. Schlenger, D. L., Riddle, W. F., Luck, B. K., Winter, M. H. (1996). Automation Management Strategies for Water Treatment Facilities. American Water Works Association Research Foundation Report No. 90676. Denver, CO. 195 p.

4. Shariff, R., A. Cudrak, S. Stanley. 2001. Remote Monitoring and Operation of Isolated Facilities in Cold Regions. Proceedings, AWWA Annual Conference, Washington D.C., June 2001.

5. USEPA (United States Environmental Protection Agency). 2001. FY2000 IB SDWIS/FED Factoids. <www.epa.gov/safewater/data/00factoids.pdf>

6. Willis, M. J. and Tham, M. T. (1994). Advanced Process Control, <http://lorien.ncl.ac.uk/ming/advcontrl/apc.htm >

2.0 LIME SOFTENING CLARIFIER MODELING WITH ARTIFICIAL NEURAL NETWORKS

2.1 Introduction

Water softening involves the removal of multivalent dissolved metallic cations in water also known as hardness. It is practiced in some drinking water treatment plants where the level of hardness in the water is considered high. The term "hardness" is also used to characterize water that does not lather well, causes a scum in bath tubs, and leaves hard, white, crusty deposits (scale) on coffee pots, tea kettles, and hot water heaters (Davis and Cornwell, 1998). Higher levels of hardness require higher amounts of soap to produce lather.

The pre-dominant cations present in water are calcium and magnesium and where this is the case, the total hardness of water is simply the sum of the calcium and magnesium ions expressed in mg/L as $CaCO_3$ equivalent. Waters are commonly classified in terms of the degree of hardness – the higher the number, the more hard the water. Table 2-1 illustrates this further.

TABLE 2-1 Degree of hardness of water (after Sawyer et al, 1994)

Hardness mg/L as $CaCO_3$	Degree of hardness
0 to 75	Soft
75 to 150	Moderately hard
150 to 300	Hard
300 up	Very hard

The degree of hardness of water depends greatly on where the water originates. In general, hard waters originate in areas where the topsoil is thick and there is a presence of limestone formations whereas soft waters originate where the topsoil is thin and there is an absence of limestone formations (Sawyer et al, 1994).

Aside from the obvious aesthetic value of softening for the general public, industries are particularly concerned about the scale-forming potential of water in equipment such as boilers, heaters and pipes. Scale formation in such equipment reduces heat transfer rates and clogs pipes leading to lower efficiencies and increased energy costs. The hardness ions can also contribute colour or influence the taste of products made from the water and so industries often treat water beyond the standards of municipal water supplies (Droste, 1997).

The reduction of hardness is commonly done with a chemical precipitation process such as the lime-soda ash process or through an ion exchange process (Benefield et al, 1982). The chemical precipitation process using lime-soda ash requires large investments in equipment and on-going operating costs. The investments can include equipment to receive, prepare and inject the lime and soda ash chemicals, mixing of the chemicals, flocculation, sedimentation, filtration, pH adjustment, recycling of solids, removal of solids from the sedimentation basins, concentration of the solids in a thickener and/or centrifuge and the final disposal of the sludge. Water treatment plant softening clarifiers are typically operated in manual mode with corrections made when problems occur or if the parameters such as hardness, pH, or turbidity are outside the operating range (which are usually set quite wide). It is thought that optimization as well as consistent operation of the softening process would improve the overall quality of the water, narrow the operating range of the parameters and lead to better control of the costs of operation. To achieve these goals, modeling of the softening process becomes necessary.

This chapter examines the application of the artificial neural network (ANN) modeling technique to model a softening process at a full-scale drinking water treatment facility. The modeling was done for the Rossdale Water Treatment Plant (WTP) operated by EPCOR Water Services Inc. in Edmonton, Alberta, Canada.

2.1.1 Modeling of Processes

Modeling of water treatment plant processes can serve many purposes. In general, modeling of processes becomes necessary for plants aiming to automate operations while also optimizing water quality and costs. For a plant operator, a working model of the process facilitates investigation of system response to a wide range of inputs without jeopardizing actual system performance. For the controls engineer, an accurate depiction of a process in real time, i.e., a dynamic model, is a necessity if the process is to be placed on automatic control. For the design engineer, a model permits the development of near optimal designs at minimal cost. For a researcher, models form a framework upon which to build and test hypotheses. For plant management staff, models provide the ability to test "what if" scenarios be they quality based (brought about by new regulations), cost based (due to budget constraints), production based, or planning based (both short and long term).

Forms of models range from the highly mechanistic type which are most useful for understanding the system, to the highly empirical which are most useful to an operator because they reflect the "real world" (Patry and Chapman, 1989). Empirical models are based on an inductive or data-based approach while mechanistic models are based on a deductive or theoretical approach involving theoretical relationships or organizing principles (Chapra, 1997). Purely empirical models are highly system and/or site specific and are therefore not easily adaptable to new situations. Accurate mechanistic types of models are therefore more desirable but they can be difficult to develop.

According to Chapra (1997), for both empirical and mechanistic models, the cost of modeling can become quite expensive and there also exists trade-off between model complexity, uncertainty, and information as depicted in Figure 2-1. In this figure, the straight line indicates (assumes) that with an unlimited budget available, a more complex model will be more reliable. Since an unlimited budget is not generally available, one must make do with limited data. This can produce two extreme outcomes: one occurs when a model is so simple that it cannot produce reliable results and the other is when a model is so detailed that it outpaces available data. In both cases, the models are unreliable. There does exist an intermediate point (shown as the middle trend in Figure 2-1) where the model is consistent with the available level of information. Therefore, one needs to strive to develop the simplest model that is consistent with the data and the problem requirements.

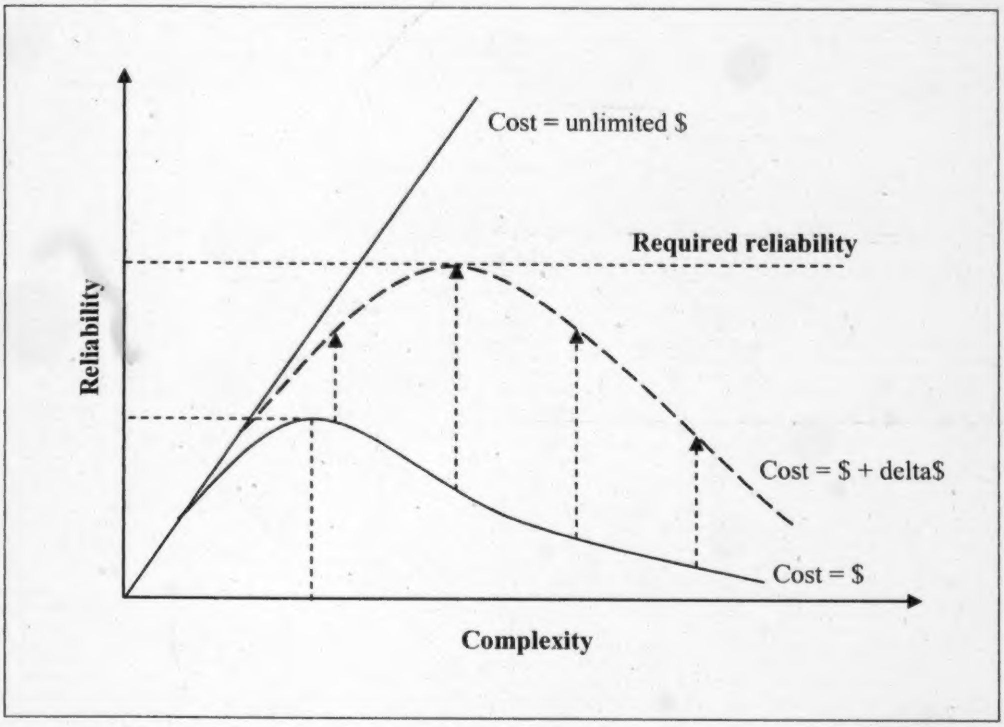


FIGURE 2-1 Trade-off between model reliability and complexity (after Chapra, 1997)

For the water softening process in Edmonton, the use of both simpler models developed in-house as well as available detailed software models (but limited in what site-specific inputs it will accept) have led to inaccurate predictions to date. The use of the ANN technique has not been applied to the softening process thus far and due to its ability to easily accept more information that is site-specific to the plant, it was hoped that it will provide predictions that are reliable and consistent with the data available.

Regarding the inductive approach to modeling, it has been shown by Zhang (1996) that an inductive learning process (learning from examples of its inputs and outputs such as the ANN modeling approach) is possible if sufficient learning samples (data) are provided. What remains then is to balance the need for sufficient data for the ANN with the requirements of the problem to achieve a certain level of reliability.

2.1.2 Project History and Scope

In the spring of 1997, EPCOR Water Services Inc. (then known as Aqualta) Edmonton, Alberta, Canada was contemplating increasing the target value of total hardness from an approximate average of 115 mg/L to 135 mg/L (as $CaCO_3$) or even higher in the drinking water supply to its customers. EPCOR Water Services Inc. (EWSI) wanted to have an idea of what the impact of this move might be in terms of the usage of lime, carbon dioxide, and sludge production. To this end, a quick estimate was made with yearly average data using the USEPA Water Treatment Plant Model software (USEPA, 1993).

Subsequent to the implementation of an increased effluent total hardness target at the water treatment plants, it was observed that the estimate from the USEPA model was substantially inaccurate. A more detailed estimate using the same USEPA model was undertaken using daily plant data and it was found that this model did not accurately reflect what was observed at the plant. Therefore, a better model was needed.

Around the same time, the Department of Civil and Environmental Engineering at the University of Alberta had produced several models for EWSI using the ANN modelling technique. One of the models was for the Rossdale WTP alum clarifier to predict effluent turbidity. The ANN technique appeared well suited for water treatment processes and so it was felt that it could be applied to model the softening clarifier at Rossdale as well. It was hoped that the ANN model would predict results more accurately than the USEPA model and could also be used in the day-to-day operation of the plant.

The specific objectives of this project were:

- To develop a model (using the ANN technique) for the softening process at the Rossdale WTP using historical daily average data for estimating, given a set of input conditions, the effluent total hardness and the lime dose requirements.
- To compare the performance of the ANN model with the USEPA model.
- To produce run time versions of the model for conducting scenario testing, and for monitoring in real time within the plant Supervisory Control and Data Acquisition (SCADA) system.

2.2 Overview of the Rossdale Water Treatment Plant

EPCOR owns and operates two water treatment plants in Edmonton, Alberta, Canada, which serve approximately 800,000 people in the area. The two plants, namely the Rossdale WTP and the E.L. Smith WTP, draw water from the North Saskatchewan River, a major tributary in the Saskatchewan-Nelson river system. Both plants utilize conventional water treatment processes and up until the spring of year 2000, included alum clarification, lime clarification, pH adjustment, chlorine disinfection, filtration, fluoridation, on-site storage and pumping.

2.2.1 Raw Water Quality and Chemical Dosage Ranges

The annual range of raw water quality parameters and chemical dosing required to treat the water at the Rossdale WTP is quite variable as shown in Table 2-2. Consequently, at certain times of the year, very quick responses by operators to changing conditions are required to maintain the stringent in-house water quality guidelines (see Table A-1 in Appendix A).

TABLE 2-2 Raw water quality and chemical dosages at the Rossdale WTP (prior to spring 2000)

Raw water quality parameters; chemical dosages	Unit	Low	High	Average
Turbidity	NTU	1	> 3500	40
Colour	TCU	2	100	12
Alkalinity (as $CaCO_3$)	mg/L	96	155	130
Total Hardness (as $CaCO_3$)	mg/L	96	197	161
Temperature	deg C	0	25	9
pH		7.8	8.6	8.2
Alum dose	mg/L	9	280	43
Polymer (Allied Colloids LT27) dose	mg/L	0.16	0.53	0.31
Powdered activated carbon dose*	mg/L	5	195	15
Lime (CaO) dose	mg/L	22	92	46
Chlorine dose	mg/L	2.2	4.5	2.8
Fluoride dose	mg/L	0.6	0.9	0.75
CO_2	mg/L	0	12	2.5
Aqua ammonia	mg/L	0.60	0.90	0.75

*Used during taste and odour events only

The highly variable raw water quality has been categorized by the plant operations staff into six distinct raw water types as shown in Table 2-3. For each type of water, the plant production capacity is different due to differences in treatment challenges. The most difficult treatment occurs during the spring run-off (Type 2) condition due to a higher level of organics and taste and odour compounds present in the raw water. The most common type of raw water quality is summer normal (Type 5) accounting for 43% of the total.

TABLE 2-3 Typical raw water conditions and production rates for the Rossdale WTP's (prior to 2000)

Raw Water Type	Plant 1 ML/d	Plant 2 ML/d	Turbidity NTU	Colour TCU	Alkalinity mg/L	Total hardness mg/L	Temp deg C	pH	% of time
1 winter	70	105	< 25	> 0	130	160	< 5	8.1	37
2 spring run-off	50	75	< 25	> 35	110	130	< 5	8.0	3
3 spring break-up	75	115	> 25	> 0	120	150	< 5	8.1	5
4 summer rains	70	105	50 - 200	> 0	130	150	> 5	8.2	4
5 summer normal	105	155	< 50	> 0	110	150	> 5	8.3	43
6 summer flood	70	105	> 200	> 0	120	150	> 5	8.2	8

2.2.2 Treatment Process Units

At the Rossdale WTP, two similar trains exist each with an alum clarification stage followed by a softening clarification stage, recarbonation, disinfection, and filtration. The two trains, known as Plant 1 and Plant 2, have a maximum production capacity of 120 ML/d and 170 ML/d, respectively. Each train comprises two square cross-flow clarifiers with three tapered flocculation stages and a sedimentation stage with tube settlers. Recarbonation and disinfection is carried out in stilling basins and then the water from both trains is combined prior to filtration. The on-site storage capacity for treated water is 100 ML. A process schematic for the Rossdale WTP is shown in Figure 2-2.

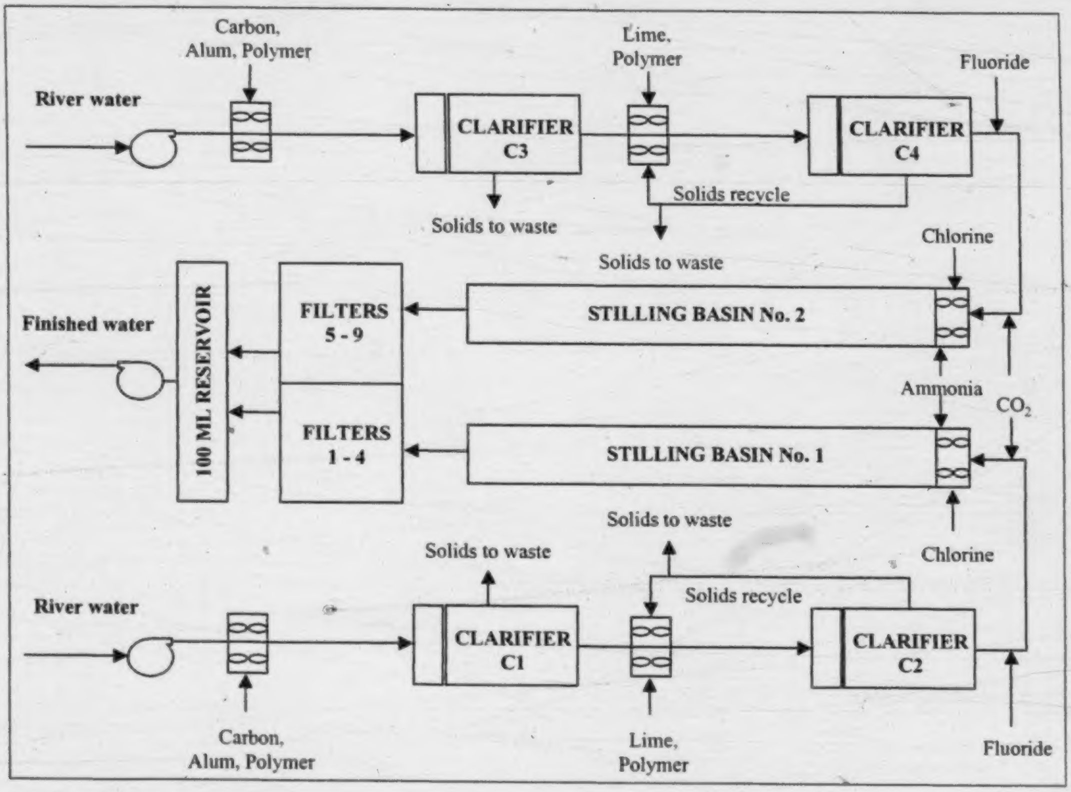

Carbon,
Alum, Polymer
Lime,
Polymer
Fluoride
River water
CLARIFIER
C3
CLARIFIER
C4
Solids recycle
Solids to waste
Solids to waste
Chlorine
Finished water
100 ML RESERVOIR
FILTERS
5 - 9
STILLING BASIN No. 2
Ammonia
CO2
FILTERS
1 - 4
STILLING BASIN No. 1
Solids to waste
Solids to waste
Chlorine
Solids recycle
River water
CLARIFIER
C1
CLARIFIER
C2
Carbon,
Alum, Polymer
Lime,
Polymer
Fluoride

FIGURE 2-2 Process schematic for the Rossdale Water Treatment plants (pre 2000)

Water treatment at the Rossdale WTP up until early 2000, was conducted in the following six major process units:

- Low Lift Pumphouse
- Alum Clarifier
- Lime Clarifier
- Stilling Basin
- Filtration
- On-site reservoir and pumping station

A brief description of each major unit process is provided in the following sections.

2.2.2.1 Low Lift Pumphouse

Raw water is drawn from the North Saskatchewan River into inlet wells located in the Low Lift Pumphouse building. The raw water passes through a set of traveling water screens to remove larger branches, twigs, and fish prior to it entering into pumping wells. The raw water is pumped from the pump wells into the plants' alum clarifiers.

2.2.2.2 Alum Clarifier

The first stage treatment occurs in a set of cross-flow square alum clarifiers. Prior to the water entering the clarifier, liquid alum is injected into the water at a rapid mixer unit to destabilize and coagulate the colloidal particles in the water. During taste and odour events, powdered activated carbon is also added to the raw water at the rapid mixer. An anionic polymer (Allied Colloids LT27) is added just before the coagulated water enters the three tapered flocculation stages where gentler mixing of the water occurs to promote floc formation. The water then flows to the sedimentation portion of the clarifier where tube settlers assist with particle settling. A slow-moving rake at the bottom of the clarifier moves the settled particles towards the center of the clarifier where they are removed with pumps on an intermittent basis depending on the solids loading. The alum dosage is varied based on the incoming raw water quality parameters such as turbidity and colour and as well on the performance of the clarifier effluent and overall plant performance after filtration. The dosage of alum required is estimated by the operators based on jar tests and operator experience.

The total volume of the clarifier including the flocculation and sedimentation sections and theoretical residence times are given in Table 2-4. Both the alum and lime clarifier volumes in each plant are approximately the same size.

TABLE 2-4 Clarifier volumes and residence times for the Rossdale WTP's.

	Plant 1 (alum or lime clarifier)	**Plant 2** (alum or lime clarifier)
Volume (ML)	6.8	11.2
Residence time at 50 ML/d (min)	196	-
Residence time at 100 ML/d (min)	98	161
Residence time at 170 ML/d (min)	-	95

2.2.2.3 Lime Clarifier

Once the water has been treated in the alum clarifier, the effluent is diverted to the lime clarifier where another rapid mixer is located just prior to the flocculation section. At the rapid mixer, lime, anionic polymer (Allied Colloids LT27), and lime solids recycled from the bottom of the lime sedimentation section are injected. The flocculation and sedimentation sections are very similar to the alum clarifier described in section 2.2.2.2 including the volumes and residence times as given in Table 2-4. Settled solids not recycled are pumped on an intermittent basis to a thickener followed by centrifugation and final disposal.

2.2.2.4 Stilling Basin

The effluent from the softening clarifiers enters two stilling basins of equal volumes (6.1 ML). A number of chemicals are added at the inlet of the basins with very short delays in between including (in order): Fluoride (as H_2SiF_6), CO_2 for pH adjustment, chlorine and ammonia (NH_4OH) for disinfection. The stilling basins provide additional settling time for particles, disinfection contact time, improved water stabilization following pH adjustment, and as well help buffer any upsets occurring in the softening clarifiers.

2.2.2.5 Filtration

The effluent from each stilling basin enters a common filter influent flume where the water from each plant is allowed to mix prior to filtration. A total of nine mono-media (crushed-quartz) rapid sand filters are available. Air scouring and backwashing of the filters is carried out if the effluent turbidity, particle counts, or on-line time exceeds a preset value.

2.2.2.6 On-site Reservoir and Pumping Station

Filter effluent water is stored in two on-site underground 50 ML reservoirs prior to being pumped out by the High Lift pumps into the distribution system where additional storage and pumping stations divert the water where needed in the city. The on-site reservoirs provide additional disinfection contact time and about half a days worth of treated water production buffer volume.

2.2.3 Softening Clarifier Process Control

At the Rossdale water treatment plant, partial softening is carried out through chemical precipitation in the second clarifier of each plant. At the rapid mixer influent to the clarifier flocculation section, the following is injected:

- Lime slurry prepared on-site by converting quicklime powder (CaO) to slaked lime ($Ca(OH)_2$).
- An anionic polymer prepared on-site by batching the powdered form of the polymer (Allied Colloids LT27) to liquid.
- A portion of the settled lime solids from the bottom of the sedimentation basin (recycling).

2.2.3.1 Process Variables

The process variables managed by the operators include the softening clarifier effluent total hardness and turbidity. It is desirable to keep the effluent turbidity at a value less than 3 NTU. Higher values are an indication of poor overall performance of the softening clarifier. This can lead to increased usage of CO_2 in the stilling basin for pH adjustment and as well, filter performance problems. The effluent total hardness average target has typically been set to 115 mg/L in the past years although, in mid-1997, the target was raised to about 135 mg/L. During challenging raw water conditions such as spring runoff or break-up, the incoming raw water total hardness can be less than 100 mg/L and so the softening clarifier effluent hardness targets are not achieved during those times.

2.2.3.2 Control Variables

The control variables that can be manipulated by the operators include:

- lime dose;
- polymer dose;
- recycle flow rate, waste flow rate, and density of solids;
- flocculator mixer speeds and tapering level between the three flocculator stages; and
- water flow rate through the clarifier.

The dosage of lime is mostly determined from operator experience and rules of thumb. One rule is if the alum dose in the alum clarifier is increased by 2 mg/L then the lime dose should be increased by 1 mg/L. The dose is corrected as required based on the measured effluent total hardness values.

The polymer dose is varied mostly on a trial-and-error basis based on solids settling and effluent turbidity performance.

It has been observed by the plant operations staff that recycling of solids greatly improves the efficiency of the softening reaction and the effluent turbidity of the cross-flow clarifier. The solids recycle and waste rates are adjusted as required on a trial-and-error basis to maintain a certain range of solids density (as measured by sludge volume index, SVI, tests) and to improve the settling characteristics of the solids.

The water flow rate through the clarifier is the same as the incoming raw water flow rate to the plant. The water flow rate can be varied based on the capacity of the plant for a given raw water type. Generally speaking, at higher flow rates the performance of the clarifier can deteriorate. Although the raw water flow rates can be varied based on clarifier performance, ultimately, the flow rates are dictated by the customer demand for drinking water.

Once an acceptable level of performance is attained, the flocculator speeds are seldom adjusted on a day-to-day basis. The speeds may be lowered or raised to balance excessive settling in the floc chambers (due to low impeller speeds) with shearing of the floc (due to high impeller speeds) which can lead to settling problems and floc carry over.

Overall, a visual inspection of the clarifier and solids quality along with hardness and pH tests are used in making decisions about varying the control variables. It has also been observed that the carry over of floc from the alum clarifier has an influence on the softening clarifier. Some carry over can have beneficial results while excessive carry over can be detrimental. However, control of carry over is not done in any systematic manner.

2.3 Lime Softening

The primary goal of water softening is to reduce the dissolved minerals thereby reducing scale-forming tendencies and consumption of household cleaning agents. There are however other benefits (AWWA, 1998) including:

- removing radium 226 and 228;
- removing heavy metals;
- removing certain organic compounds and reducing total organic carbon (TOC);
- removing iron and manganese; and
- increasing the Langelier Saturation Index, useful for corrosion control in the distribution system.

The primary chemical used for water softening is lime (AWWA, 1998) which is also the chemical used at the Rossdale WTP. Accurate determination of the required amount of lime for a given situation in a plant environment can be difficult due to a number of complex and dynamic chemical interactions that are involved in lime softening. For a given removal of hardness in a water, the cost of lime and the associated costs for residuals handling can be substantial and so optimization of the process can yield not only improved costs of operation but also improved quality.

2.3.1 Classification of Hardness

Hardness can be classified in two ways: (1) with respect to the metallic ions such as Ca^{2+}, Mg^{2+} and (2) with respect to the anions associated with the metallic ions. Table 2-5 describes this further.

TABLE 2-5 Hardness definitions

Type of hardness	**Description**
Carbonate hardness	Hardness chemically tied with bicarbonate and carbonate alkalinities (formerly known as temporary hardness).
Non-carbonate hardness	Hardness that is in excess of carbonate hardness (formerly known as permanent hardness).
Calcium hardness	The portion of the total hardness due to the calcium ion.
Magnesium hardness	The portion of the total hardness due to the magnesium ion.
Total hardness	Carbonate hardness + Non-carbonate hardness. Typically, total hardness in water is the sum of the calcium and magnesium ions.

Alkalinity is a measure of the capacity to neutralize strong acid, and in natural waters, it is mostly attributable to bases such as carbonate (CO_3^{2-}), bicarbonate (HCO_3^-), and hydroxyl (OH^-) (Snoeyink & Jenkins, 1980). Since alkalinity and hardness are both expressed in terms of $CaCO_3$, the following relationship between alkalinity and carbonate hardness exists (Sawyer et al, 1994):

If total alkalinity < total hardness then: Carbonate hardness = alkalinity

If total alkalinity > total hardness then: Carbonate hardness = total hardness

2.3.2 Chemistry of Softening

The carbonic acid system is important to the chemistry of softening and a graphical representation of it is shown in Figure 2-3.

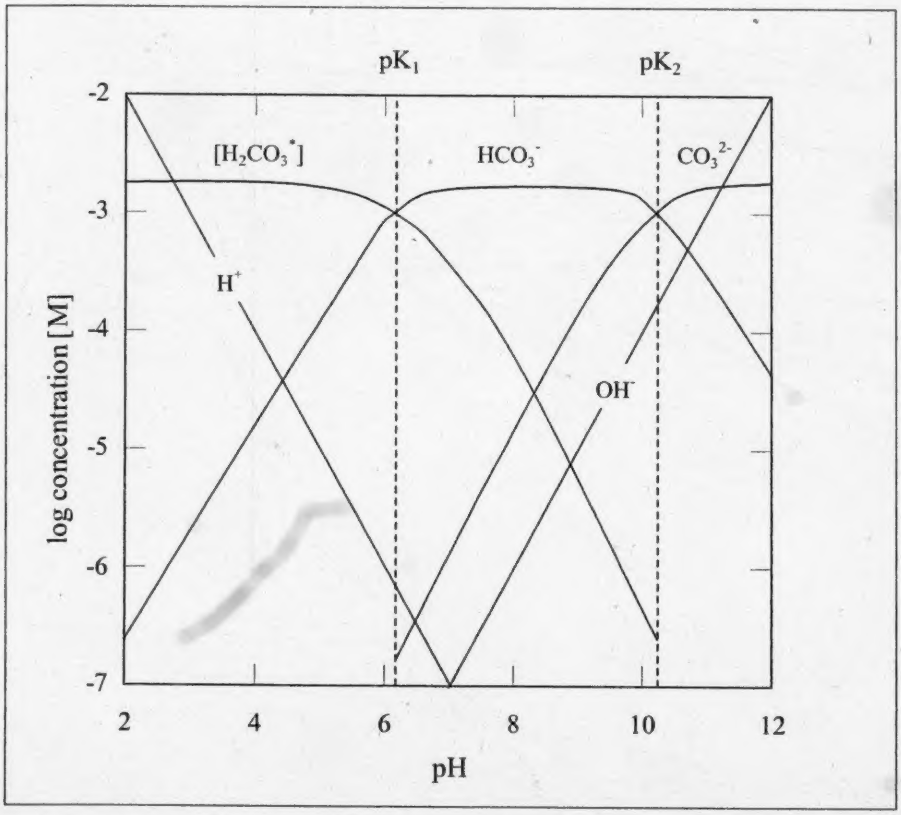


FIGURE 2-3 Effect of pH on the species composition of a carbonic acid system (after Benefield, 1982)

For most natural waters including Edmonton's, the pH is around the neutral range and assuming that the alkalinity in the water is mainly due to the carbonic acid system, the dominant species, as seen in Figure 2-3, would be bicarbonate (HCO_3^-) alkalinity. The goal of softening is to reduce hardness, of which carbonate hardness is the most important for Edmonton's water. The equilibrium equation for calcium carbonate describes the major compound that is precipitated:

$$CaCO_{3\,(s)} \Leftrightarrow Ca^{2+}{}_{(aq)} + CO_3^{2-}{}_{(aq)} \tag{2.1}$$

Now, when lime ($Ca(OH)_2$) is added to water, it dissociates as follows:

$$Ca(OH)_2 \Leftrightarrow Ca^{2+} + 2OH^- \tag{2.2}$$

The hydroxyl ion (OH^-) in Equation 2.2 elevates the pH of the water. Referring to Figure 2-3 again, this increase in pH will shift the equilibrium of the carbonic acid system so that the dominant species (alkalinity) now becomes the carbonate ion (CO_3^{2-}) instead of bicarbonate (HCO_3^-). Complete conversion of bicarbonate to carbonate occurs around a pH of 12. The corresponding effect on Equation 2.1 with this increased level of carbonate ion is governed by Le Chatelier's principle and the equilibrium shifts to the left. That is, more calcium carbonate ($CaCO_3$) will precipitate and so a *decrease* in soluble Ca^{2+} must occur. The reduction of Ca^{2+} ion is how the calcium hardness is reduced in the softening stage.

The theoretical limit of calcium reduction using lime depends on the amount of carbonate ions that can be generated to react in Equation 2.1. The amount of carbonate ions that can be generated in turn depends on the amount of alkalinity (bicarbonate usually) initially present in the water. Therefore, alkalinity plays a key role in softening reactions. When lime is used for softening, it can only remove the *carbonate* portion of the total hardness be it caused by the calcium or magnesium ions. To remove *non-carbonate* hardness such as $CaSO_4$, carbonate ions from an external source such as soda ash (Na_2CO_3) must be added.

In terms of how much lime is required for softening, there is one more important reaction that takes place before any softening can occur and that is the reaction of lime with the dissolved CO_2 which is always present in water:

$$CO_2 \quad + \quad Ca(OH)_2 \quad \Leftrightarrow \quad CaCO_{3\,(s)}\downarrow \quad + \quad H_2O \qquad (2.3)$$

Equation 2.3 imparts an initial lime demand with no corresponding hardness reduction and must be considered in lime dose calculations. Once this reaction is satisfied, the following reaction summarizes the removal of calcium hardness with lime:

$$Ca(HCO_3)_2 \quad + \quad Ca(OH)_2 \quad \Leftrightarrow \quad 2CaCO_{3(s)}\downarrow \quad + \quad 2H_2O \qquad (2.4)$$

Equation 2.4 shows that one equivalent of lime will remove one equivalent of carbonate hardness.

In this discussion, removal of magnesium carbonate hardness was not covered. In order to remove magnesium carbonate hardness with lime, the bicarbonate alkalinity in excess of the amount associated with calcium carbonate hardness must first be neutralized before the hydroxyl ion (OH^-) can be increased sufficiently for magnesium removal (Benefield et al, 1982). This is represented by the higher-pH region in Figure 2-3. The overall reaction for removal of magnesium carbonate hardness is as follows (Montgomery, 1985):

$$Mg(HCO_3)_2 \quad + \quad 2Ca(OH)_2 \quad \Leftrightarrow \quad Mg(OH)_{2(s)}\downarrow \quad + \quad 2CaCO_{3(s)}\downarrow \quad + \quad 2H_2O \qquad (2.5)$$

In normal operation at the Rossdale WTP, magnesium hardness removal is insignificant due to the fact that generally the amount of hardness to be removed to meet plant effluent criteria is less than the amount of calcium carbonate hardness present in the water.

2.3.3 Lime Dose Calculations

Several methods are available that can be employed in the calculation of the chemical dosages required for lime softening. Three of these methods are: stoichiometric calculations, Caldwell-Lawrence diagrams, and equilibrium calculations (Benefield, 1982). The stoichiometric methods assume that the reactions represented by the softening equations go to completion. The Caldwell-Lawrence diagrams are a graphical method for arriving at chemical requirements based on equilibrium principles. The equilibrium calculation method is an alternative to the Caldwell-Lawrence diagrams. It applies basic equilibrium concepts to describe the mechanisms of the water softening and neutralization processes as well as to calculate the required chemical dosages.

Computer software programs that incorporate the lime dose calculation methods mentioned above are also available including one from the USEPA called the Water Treatment Plant Model (USEPA, 1993). As mentioned earlier, this particular software was tested prior to this study and it was found to inaccurately predict the lime dosage values when compared to what the Rossdale plant clarifier actually used. One reason for this is that the calculations that the software makes are at best an estimate of the actual reactions. Another likely reason is the fact that the specific information about the plant such as mixing efficiency, lime preparation efficiency and particle quality, sludge blanket effects, operator preferences in running the clarifier, water flow-rates and rise rates, and so on are not all available or quantifiable and even if they were, the software program is not designed to accept all of this information. This was one of the reasons why the artificial neural network modeling technique was envisioned as it is capable of learning the actual performance of the plant first prior to making predictions of what the required lime dosage would be for a given situation. The lime dose calculation based on this method would be site specific and would likely not be usable at another water plant without first providing it with specific performance examples of the new site. This disadvantage is offset in that the more accurate predictions could lead to improved process control, automation, and cost control.

2.4 Artificial Neural Networks

2.4.1 Introduction

An Artificial Neural Network (ANN) is an artificial intelligence (AI) modeling technique inspired by the structure and operation of a human brain (Rodriguez et al, 1997). It is an empirical model (as opposed to a mechanistic model) and is somewhat unique in that the technique learns from representative historical data characterizing a given process.

Compared to conventional modeling approaches, the ANN approach to modeling has several advantages (Zh[illegible]ng & Stanley, 1997, Rodriguez et al, 1997):

- No mathematical algorithms are required to build a model. The ANN self organizes itself and learns from previous sample data.
- Models can be generated quickly compared to building physical models.
- Since the models are developed using actual process data, model scale-up is not required and therefore the potential for inaccuracies created due to it is avoided.
- An ANN can handle non-linear relationships well due to its inherent non-linear data structure and computational process. Thus it is able to identify the intricacies of a process and discover and establish complex non-linear relationships between input and output variables.
- ANN's tend to be inherently fault-tolerant due to the data structure being loosely organized.

It is important to recognize that ANN modeling is appropriate in some situations and may fail dramatically in others. Successful ANN applications tend to have the following characteristics (Zhang & Stanley, 1997): (1) the algorithm to solve the problem is unknown or expensive to discover; (2) heuristics or rules to solve the problem are unknown or perhaps difficult to enunciate; and (3) the application is data-intensive and a variety of data describing the subjects are available. On the other hand, ANN modeling will likely be unsuitable for cases where precise mathematical computations are required, where computational procedures must be explained, or adequate representative data are not available.

2.4.2 ANN Model Components

The fundamental processing elements of a neural network are neurons, which are highly interconnected with each other within the network. The neurons are also organized in three separate layers: an input layer, a hidden layer, and an output layer. In Figure 2-4, a schematic of a simple ANN is shown which illustrates these two main features along with an error back-propagation system, which is active during the learning phase.

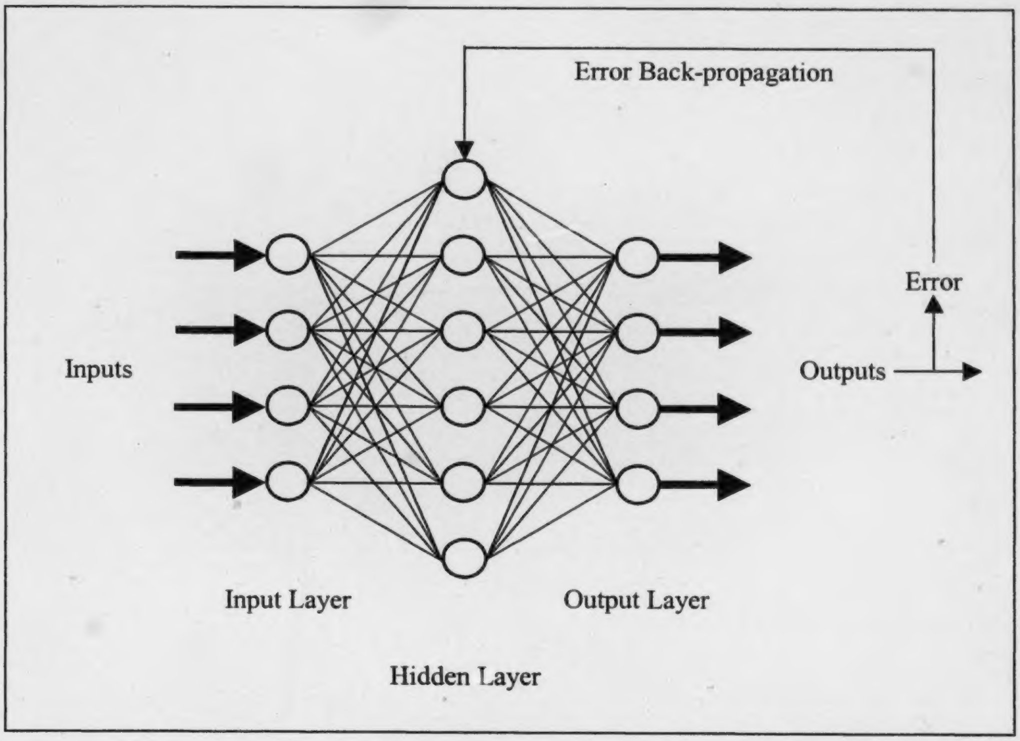

Error Back-propagation
Error
Inputs
Outputs
Input Layer
Output Layer
Hidden Layer

FIGURE 2-4 A simple artificial neural network (after Zhang, 1996)

2.4.2.1 Artificial Neurons

An artificial neuron, shown schematically in Figure 2-5, is comprise of input(s), a processing unit, and output(s). Basically, the artificial neuron receives inputs from other sources, combines them in some way (weights), performs a generally non-linear operation on the result (activation or transfer function), and then outputs the final result. The inputs can come from other artificial neurons and the outputs are passed to the next neurons.

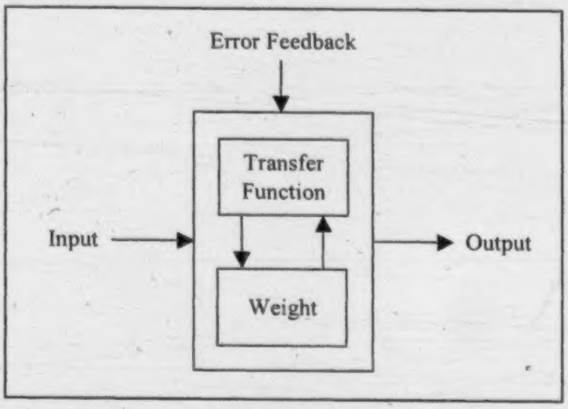


FIGURE 2-5 An artificial neuron (after Zhang, 1996)

2.4.2.2 Network Layers

As shown in Figure 2.5, a simple but common type of artificial neural network consists of three layers:

Input Layer – Represents the raw information that is fed into the network. The input layer is connected to the hidden layer.

Hidden Layer – The activity of each hidden neuron is determined by the activities of the input neurons and the weights on the connections between the input and hidden neurons. The hidden layer is where the majority of the processing is done (Hasham, 1998).

Output Layer – The behaviour of the output neurons depends on the activity of the hidden neurons and the weights between the hidden and output neurons.

This simple representation of an ANN is interesting because the hidden neurons are free to construct their own representations of the input. The weights between the input and hidden neurons determine when each hidden neuron is active, and so by modifying these weights, a hidden neuron can choose what it represents (Stergiou & Siganos, 1996).

2.4.2.3 ANN Learning with Error Back-propagation

Before the ANN model is usable, learning has to take place. There are two learning techniques that can be used – supervised learning and unsupervised learning. The supervised learning technique requires that both the input and its corresponding output data are presented to the ANN. In unsupervised learning, there are no available actual output values for a given set of inputs and so during the learning process, the network adjusts itself to the statistical regularities of the input data so that is can form categories (Stanley et al, 2000).

The most common supervised learning algorithm is the back-propagation algorithm, in which a data set of system inputs and outputs are presented to a neural net having initial connection weights assigned. An error is calculated from the network output, compared with the known output, and the connection weights are modified to decrease the sum of squared error. The process in repeated, as illustrated in Figure 2-6, until the ANN is considered to have learned as tested by a previously unseen data set that gives an acceptable small error (Boger, 1992).

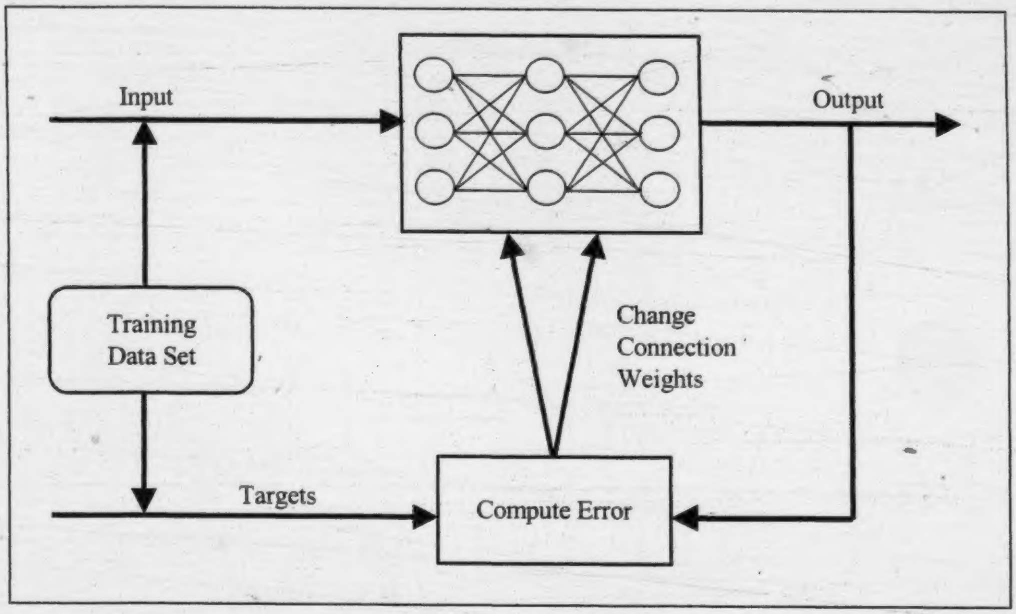


FIGURE 2-6 **Data flow in error back-propagation training of ANN (after Boger 1992)**

2.5 Model Development and Evaluation

One of the main goals of this study is to be able to predict, given a set of input conditions, the total hardness (process variable) exiting the lime softening clarifier and as well the required lime dose (control variable) to achieve a total hardness target value. This requires that two types of models be developed – forward models and inverse models.

2.5.1 Forward and Inverse Models

Forward modeling of a process involves mapping the forward dynamics of the process. The output of a forward model is the process variable, which for the softening process is the effluent quality of the clarifier namely, total effluent hardness. Therefore, forward modeling predicts the outcome of a unit process at some future time given a set of inputs to the unit process.

Inverse modeling of a process on the other hand involves mapping the inverse dynamics of the process. The output of an inverse model is a control variable, which for the softening process is the lime dose being applied at the inlet of the clarifier. Therefore, inverse modeling of a softening process predicts a value of the control variable (lime dose) that will be necessary to achieve some target value of the process variable (total hardness).

Using the softening process for illustration, the inputs and outputs for forward and inverse modeling are shown in Figure 2-7. In terms of integrating models into a control system, the output from an inverse model can be integrated directly (direct control) as it predicts the required value of the control variable (lime dose) directly which can be passed over, as is, to the lime feeder controls. The output from a forward model cannot be integrated directly in this way and an iterative process must be set up to determine the control variable indirectly which can then be passed over to the lime feeders.

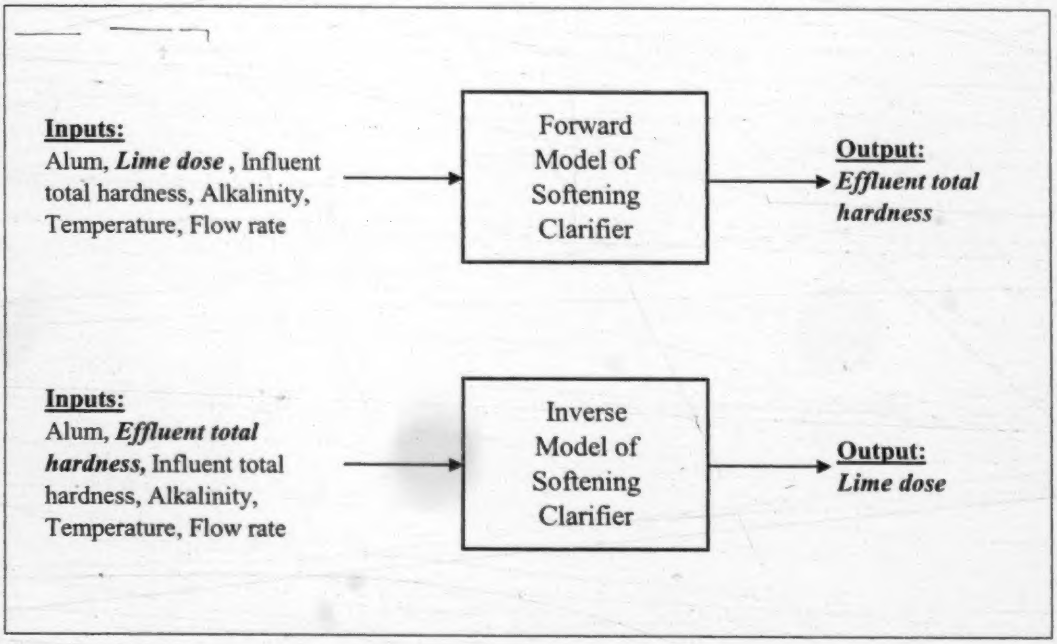

Inputs:
Alum, Lime dose, Influent total hardness, Alkalinity, Temperature, Flow rate
Forward Model of Softening Clarifier
Output:
Effluent total hardness
Inputs:
Alum, Effluent total hardness, Influent total hardness, Alkalinity, Temperature, Flow rate
Inverse Model of Softening Clarifier
Output:
Lime dose

FIGURE 2-7 Forward and inverse model architecture for a softening process

2.5.2 Modeling Protocol

In developing ANN models, there is no set standard protocol that is predominantly in use. Instead, researchers tend to develop their own methods based on what works best. There are protocols that have been developed for drinking water treatment processes and river water quality forecasting by Zhang (1996) and Stanley et al. (2000) that seem to work well. In this study, a three step process that is somewhat similar to the protocol described in the above references is followed, and includes source data analysis, model design, and model evaluation.

Source Data Analysis

Before ANN modeling can begin, an analysis of the source data is the recommended first step. Among other things, source data analysis helps with determining what data is available and relevant and whether the ANN technique is appropriate for the problem at hand. Potential input and output parameters can be chosen by identifying suspected cause-effect relationships between parameters even though the actual mechanism may not be fully understood. For example, it is known that the initial alkalinity present in an alum clarification process affects the final effluent pH and so are potential cause-effect parameters. In the source data analysis, data cleansing is done to identify and root out data patterns that are unusable. This could be due to sensor failures, equipment servicing, data patterns with only partial data, and unstable operational data such as during plant-start-ups and shut-downs.

Model Design

In the model design stage, an appropriate ANN architecture is chosen to provide optimum performance from the ANN models. This involves choosing the type of network (e.g. back-propagation), learning methods (supervised versus unsupervised) and speed, the number of inputs, outputs, hidden layers, and neurons, and the type of activation function used by the neurons.

To improve the capability of the ANN model to make accurate predictions, the available data patterns are first separated into three sets prior to the onset of the ANN model learning phase. The three sets of data are known as training, testing, and production sets.

The training set data is used by the ANN learning algorithm to train itself by repeatedly processing the data and conducting error back-propagation corrections to optimize the accuracy of the model.

The testing set data is also used by the ANN learning algorithm during the training phase to periodically evaluate the model performance on a separate set of data, to ensure that the model is not simply memorizing the data patterns in the training set, and to make corrections to move away from this tendency. The testing set data is essential for the calibration of the model.

The final set of data, known as the production set, is not used at all during the learning phase of the ANN model. It is presented to the completed model to determine the ANN model's ability to predict accurate results on data that it has not seen before.

Model Evaluation

In the model evaluation step, the performance of the various models is reviewed. A statistical analysis is completed and comparisons are made with other models that may be available such as, for the softening problem, the USEPA water treatment plant model.

2.5.3 Source Data Analysis

At the Rossdale WTP, the SCADA system records real-time information from many sensors and controls including the lime system and softening clarifier. This information can be retrieved at a later date for further review. Source data analysis therefore begins with a review of available parameters.

2.5.3.1 Available Parameters

The parameters considered available for the softening process for the Rossdale WTP are those that are measured and recorded regularly by the SCADA system or the operations staff i.e. at least once per 12 hour shift as these are the ones that the operators use to make process decisions and ultimately would be the ones used by the ANN model to predict results in real-time within the plant control system.

The parameters of interest include those related to water quality, chemical feed rates, and plant flow rates. Both continuous measurements and discrete laboratory bench tests are included in the available parameter list. A summary of measured parameters, their accuracy and the frequency of collection are given in Table 2-6. The process flow diagram given in Figure 2-2 shows the location of the various process units mentioned in this table.

TABLE 2-6 Measured parameters, accuracy, and sampling frequency

Parameter	Accuracy	Alum Clarifier Influent	Softening Clarifier Influent	Softening Clarifier Effluent	Stilling Basin Effluent
Flow rate	± 3%	Continuous	-	-	-
pH	± 0.2	4 hours	4 hours	4 hours	4 hours
Temperature	± 2%	Continuous	-	-	-
Total hardness	± 5 mg/L	4 hours	-	4 hours	4 hours
Calcium hardness	± 5 mg/L	-	-	-	6 hours
Total alkalinity	± 5 mg/L	12 hours	-	-	12 hours
Alum feed rate	± 7%	Continuous	-	-	-
Polymer feed rate	± 6%	Continuous	Continuous	-	-
Lime feed rate	± 10 to 20% estimated	-	Continuous	-	-
Recycle flow/density	± 25%	-	Continuous	-	-

The next step is to determine which of the available parameters are most relevant for modeling of the softening clarifier.

2.5.3.2 Determination of Relevant Parameters

Since the model is for the softening clarifier, ideally the relevant inputs should be measured frequently and as close to the softening clarifier influent as possible. Otherwise, issues with lag time and water quality changes in the alum clarifier (upstream of the softening clarifier) become important. However, this was not available for many of the variables. For example, as shown in Table 2-6, alkalinity is measured for the influent to the alum clarifier but not for the influent to the softening clarifier. When alum is added to the alum clarifier, it consumes alkalinity as well as lowers the pH of the water leaving the clarifier. This is illustrated in Equation 2.6 which indicates that theoretically, each mg/L of alum added will consume about 0.5 mg/L of alkalinity (Benefield et al, 1982).

$$\mathrm{Al_2(SO_4)_3.14H_2O} + \mathrm{3Ca(HCO_3)_2} \Leftrightarrow \mathrm{2Al(OH)_3} + \mathrm{3CaSO_4} + \mathrm{14H_2O} + \mathrm{6CO_2} \qquad (2.6)$$

Therefore, the alkalinity available in the softening clarifier and pH will vary considerably. The pH entering the softening clarifier is measured every 4 hours. If the alkalinity entering the softening clarifier is also important, either the alum dose should be included as one of the inputs so that the model may learn its impact or an estimate of alkalinity could be made using Equation 2.7.

$$\begin{array}{c}\text{Alkalinity in the}\\ \text{softening clarifier}\\ \text{influent}\\ \text{(meq/L)}\end{array} = \begin{array}{c}\text{Alkalinity in the raw}\\ \text{water}\\ \text{(meq/L)}\end{array} - \begin{array}{c}\text{0.5 * Alum Dose}\\ \text{(meq/L)}\end{array} \qquad (2.7)$$

The calcium hardness is not measured through the process until the effluent of the stilling basin. Therefore, it cannot be used directly as an input to the model. In fact, the amount of hardness contributed by calcium and magnesium in the influent water to the softening clarifier is unknown from the available data set.

Figures 2-8 and 2-9 show the variation of total hardness from the softening clarifier and the corresponding lime dose. Note that the total hardness increased beginning June 1997. This was due to a change in the target value of total hardness made by EPCOR Water Services from 115 mg/L to approximately 135 mg/L.

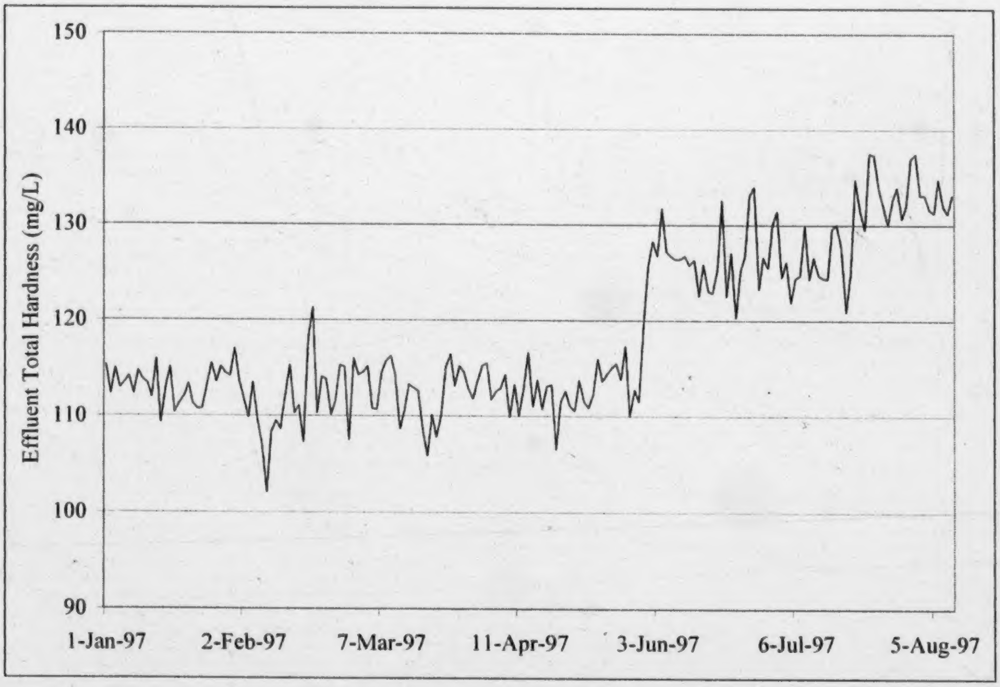


FIGURE 2-8 Softening clarifier effluent total hardness

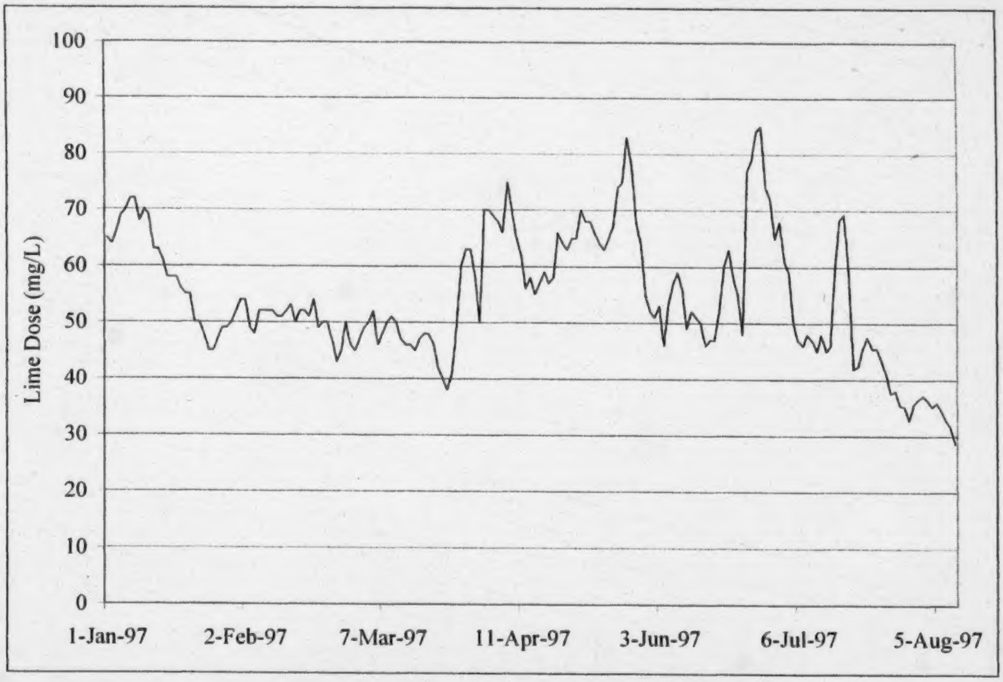


FIGURE 2-9 Softening clarifier influent lime dose

The domain of study is a closed system as the area of study (softening) is understood reasonably well and the cause-effect relationships for softening clarifier effluent hardness are also reasonably known. For example, as the raw water hardness increases, the softening clarifier effluent hardness will increase all else being equal. If the lime dose is increased, the softening clarifier effluent hardness will decrease all else being equal.

From softening chemistry principles, the important parameters available from Table 2-6 to include in the model would be: lime dose, total hardness, alkalinity, temperature and pH's. From plant experience, recycle solids, alum dose and possibly flow rate would be additional parameters to include. Since reliable data for recycle solids was not available, this parameter was not included as an input. Overall, it was envisioned that the parameters given in Table 2-7 would be important in the design of the preliminary model.

TABLE 2-7 Preliminary ANN model design parameters

Parameter	Alum Clarifier Influent	Softening Clarifier Influent	Softening Clarifier Effluent
Flow rate	Continuous	-	-
pH	4 hours	4 hours	-
Temperature	Continuous	-	-
Total hardness	4 hours	-	4 hours
Total alkalinity	12 hours	-	-
Lime feed rate	-	Continuous	-

2.5.3.3 Selection of Data Points

All the required modeling data were extracted from the plant SCADA historical data reporting system. Daily average values of each input and output formed the patterns set for the model. The historical data for the model spanned between January 1/1997 to August 08/1997.

It is critical to ensure the integrity of the input/output data patterns as it can directly affect the accuracy of the model. Therefore, careful examination of the data was conducted to remove any which were questionable. For example, in the spring of 1997 between April 19 and May 9, a temporary feed system was set up to feed soda ash. The data during this period was not used for modeling because the soda ash feed rates were not reliable and it was felt that not enough data was available for the model to learn. Data was also not used during times when the plant had just been restarted after a shutdown. For short periods of time, chlorine was being injected into the softening clarifier and data during this time was also not included in the model as it was observed that there was some detrimental impact on the performance of the softening clarifier and not enough data was available for the model to learn.

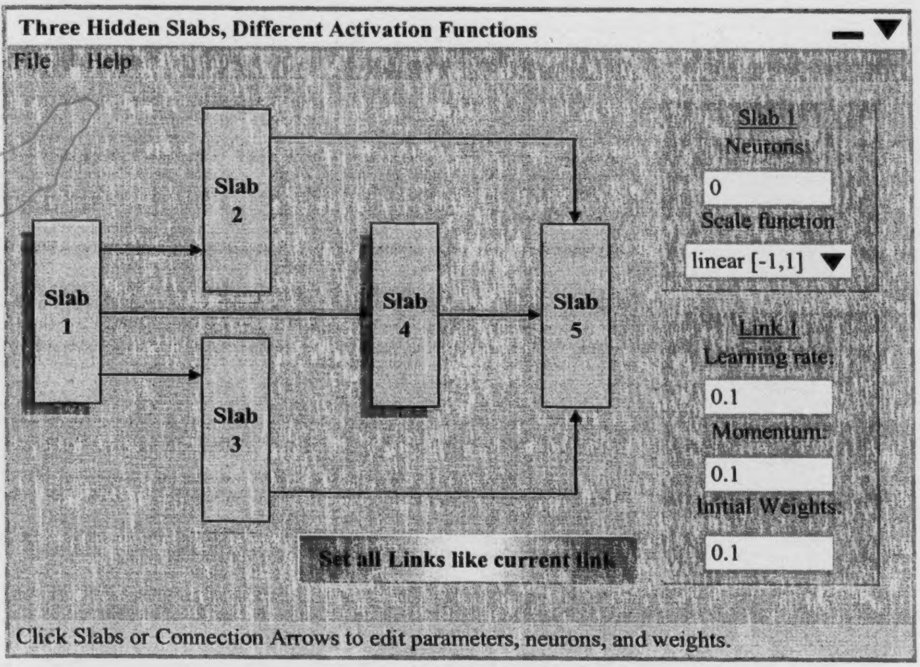
2.5.4 Model Design

Once all the data patterns have been identified, ANN modeling can begin. There are many ANN modeling software available on the market today. The software utilized in this research was the same as that used by the University of Alberta, Department of Civil and Environmental Engineering in developing previous models of the alum clarifier for the Rossdale WTP. The software is called NeuroShell2 (Ward Systems, 1996) and all modeling was carried out on a standard Personal Computer.

In the model design phase, an appropriate ANN architecture needs to be chosen. There are many to choose from including some proprietary ones. Once the architecture is chosen, what remains is to determine the number of runs that are expected to be required to achieve a reasonably accurate ANN model.

2.5.4.1 ANN Architecture

Many different topologies were initially tested including the recurrent network; three, four and five layer standard back-propagation networks; jump connection networks; and general regression networks; each with different activation functions, learning methods and rates. Although standard back-propagation (BP) networks, particularly the 3-layer network, were expected to perform the best as they have been applied to a wide variety of practical problems with proven success in modeling nonlinear relationships (Bhat and McAvoy, 1990), initial trials indicated that the 5-layer Ward network (a variation of the standard back-propagation network) was more accurate for this problem. As depicted in Figure 2-10, the network consists of 3-hidden layers, each with a different activation function. The network details are given in Table 2-8.


Three Hidden Slabs, Different Activation Functions
File
Help
Slab 1
Slab 2
Slab 3
Slab 4
Slab 5
Set all Links like current link

Slab 1

Neurons: 0

Scale function: linear [-1,1]

Link 1

Learning rate: 0.1

Momentum: 0.1

Initial Weights: 0.1

Click Slabs or Connection Arrows to edit parameters, neurons, and weights.

FIGURE 2-10 Ward 5-layer BP neural network architecture (after Ward, 1996)

TABLE 2-8 Ward 5-layer BP neural network details

ANN design and criteria parameter	**Description**
Topology	Ward back-propagation network with 3 hidden slabs
Input Slab 1	Linear function with # of neurons = # of inputs
Hidden Slab 2	Gaussian function
Hidden Slab 3	Tanh function
Hidden Slab 4	Gaussian complement function
Neurons per hidden slab	#of hidden neurons = 1/2(Inputs + Outputs) + Sqrt(# of Patterns)
Output Slab 5	Logistic function with 1 neuron
Learning rate factor	0.1 (i.e. slow)
Momentum factor	0.1 (i.e. low)
Initial weights	0.3
Pattern selection	Random
Weight update method	Momentum
Calibration	Automatic with best *test* set saved
Number of patterns for training set	65 % of total randomly extracted by NeuroShell2 program
Number of patterns test set	20 % of total randomly extracted by NeuroShell2 program
Number of patterns production set	15 % of total randomly extracted by NeuroShell2 program

2.5.4.2 Determination of the Number of Runs

Having identified the important inputs and outputs and having fixed the network topology, a set of runs was organized in a trial and error fashion. Basically, the first run consisted of using all the inputs followed by runs with a reduced set of inputs. In order to determine the influence of alkalinity reduction (due to alum) on softening, a new input: alkalinity influent to the softening clarifier, was introduced. As described in Equation 2.6, this was estimated by assuming 0.5 mg/L of alkalinity expressed as $CaCO_3$ will be consumed for every 1 mg/L of alum added.

In addition, a new neural network for predicting pH influent to the softening clarifier was also developed even though there was already data available for pH. This new network, it was envisioned, would be needed when the overall model is executed in real-time because the plant did not have an on-line pH meter influent to the softening clarifier. One would have to wait for a bench test to be completed before the model could predict the future requirements for lime dose. In essence, the pH Neural Network was designed to be a virtual pH analyzer and whenever the alum dose or raw parameters changed, it would predict the pH influent to the softening clarifier immediately thereby providing a quicker prediction of lime dose.

With the above in mind, sixteen trial runs for the overall softening process model were proposed while for the virtual pH meter neural network, a total of six trial runs were proposed. Each trial run was a unique neural network in that the combination of inputs and outputs was dissimilar. An equal number of forward and inverse models were developed. In Tables 2-9, 2-10, 2-11, and 2-12, the various trial runs are identified in terms of the neural network model inputs and outputs.

TABLE 2-9 Forward modeling trial runs for the overall softening process

ANN Inputs	SF-1	SF-2	SF-3	SF-4	SF-5	SF-6	SF-7	SF-8	ANN Output
Flow rate	x		x	x	x	x	x	x	
Alum dose	x	x			x		x	x	
Temperature	x	x	x	x	x	x	x	x	
pH - alum clarifier influent.	x	x				x		x	
Total Hardness – alum clarifier influent	x	x	x	x	x	x	x	x	
Alkalinity – alum clarifier influent	x	x		x			x		
Total hardness – softening clarifier effluent									x
Lime dose	x	x	x	x	x	x	x	x	
pH – softening clarifier influent	x	x	x	x	x	x	x	x	
Alkalinity (estimated) – softening clarifier influent								x	

TABLE 2-10 Inverse modeling trial runs for the overall softening process

ANN Inputs	SI-1	SI-2	SI-3	SI-4	SI-5	SI-6	SI-7	SI-8	ANN Output
Flow rate	x		x	x	x	x	x	x	
Alum dose	x	x			x		x	x	
Temperature	x	x	x	x	x	x	x	x	
pH – alum clarifier influent.	x	x				x		x	
Total Hardness – alum clarifier influent	x	x	x	x	x	x	x	x	
Alkalinity – alum clarifier influent	x	x		x			x		
Total hardness – softening clarifier effluent	x	x	x	x	x	x	x	x	
Lime dose									x
pH – softening clarifier influent	x	x	x	x	x	x	x	x	
Alkalinity (estimated) – softening clarifier influent								x	

TABLE 2-11 Forward modeling trial runs for the alum clarifier process (Virtual pH)

ANN Input	**pHF-1**	**pHF-2**	**pHF-3**	**ANN Output**
Flow rate	x			
Alum dose	x	x	x	
pH – softening clarifier influent				x
Temperature	x	x	x	
pH – alum clarifier influent.	x	x	x	
Alkalinity – alum clarifier influent	x	x		

TABLE 2-12 Inverse modeling trial runs for the alum clarifier process

ANN Input	**pHF-1**	**pHF-2**	**pHF-3**	**ANN Output**
Flow rate	x			
Alum dose				x
pH – softening clarifier influent	x	x	x	
Temperature	x	x	x	
pH - alum clarifier influent.	x	x	x	
Alkalinity – alum clarifier influent	x	x		

2.5.5 Model Evaluation

In the ensuing discussion, the accuracy of the models have been quoted with the R^2 error statistical indicator which is what the ANN software uses (Ward Systems Group Inc., 1996). An R^2 value of 1 implies a perfect fit. The formula for R^2 that was used is:

$$R^2 = 1 - \frac{SSE}{SS_{YY}} \qquad (2.8)$$

where $SSE = \Sigma(Y - Y_{predict})^2$

$SS_{YY} = \Sigma(Y - Y_{mean})^2$

Y = actual value of output

$Y_{predict}$ = predicted value of Y

Y_{mean} = mean of all the Y actual values

Once all the trial runs were completed, statistical indicators (described in section 2.5.5.5) were calculated to assess model performance. A summary of the performance of each of the twenty two models was prepared (Table 2-13) and are discussed in the ensuing sections.

TABLE 2-13 Performance of candidate ANN models

	Run F=Forward I=Inverse	# of Epochs reached	MinAvg Error Train Set	MinAvg. Error Test Set	R^2				Mean square error				Mean absolute error				Maximum absolute error			
					all	test	train	prod.	all	test	train	prod.	all	test	train	prod.	all	test	train	prod.
Predict C4 effluent total hardness	SF-1	14,986	0.0001	0.0032	0.92	0.93	0.94	0.94	5.4	6.2	3.7	12.0	1.8	2.0	1.5	2.7	9.0	5.1	6.9	9.0
	SF-2	15,126	0.0003	0.0030	0.92	0.94	0.94	0.83	5.5	5.9	3.8	12.8	1.7	1.9	1.5	2.7	10.9	6.1	9.3	10.9
	SF-3	15,331	0.0004	0.0049	0.91	0.89	0.93	0.84	6.6	9.7	4.5	11.7	2.0	2.4	1.7	2.8	9.9	8.9	7.1	9.9
	SF-4	17,408	0.0002	0.0047	0.90	0.90	0.92	0.84	6.7	9.2	4.9	11.4	2.0	2.3	1.7	2.6	9.1	6.7	8.8	9.1
	SF-5	17,676	0.0004	0.0033	0.92	0.93	0.93	0.85	5.8	6.4	4.4	11.2	1.8	2.1	1.6	2.4	10.4	5.0	8.9	10.4
	SF-6	18,376	0.0003	0.0051	0.88	0.89	0.89	0.84	8.3	10.1	7.0	11.8	2.2	2.5	2.1	2.6	10.1	7.4	8.8	10.1
	SF-7	19,654	0.0001	0.0033	0.92	0.93	0.93	0.84	6.0	6.6	4.5	12.1	1.9	2.0	1.7	2.6	10.6	5.3	8.6	10.6
	SF-8	12,392	0.0002	0.0034	0.92	0.93	0.93	0.86	5.8	6.6	4.6	10.5	1.9	2.1	1.7	2.5	9.6	5.4	9.5	9.2
Predicts C4 lime dose requirment	SI-1	12,186	0.0001	0.0010	0.96	0.95	0.96	0.96	5.4	5.1	5.3	6.2	1.8	2.0	1.7	2.0	7.0	4.7	7.0	4.9
	SI-2	10,341	0.0001	0.0012	0.94	0.94	0.93	0.94	8.2	6.2	9.0	7.3	2.3	2.1	2.4	2.3	7.8	6.2	7.8	5.4
	SI-3	20;308	0.0001	0.0018	0.94	0.91	0.94	0.92	8.1	8.7	7.7	9.3	2.2	2.4	2.1	2.3	10.7	6.1	10.7	8.5
	SI-4	8,399	0.0002	0.0016	0.92	0.92	0.91	0.93	10.3	8.0	11.5	7.8	2.6	2.4	2.7	2.4	8.0	6.9	8.0	5.8
	SI-5	4,578	0.0003	0.0014	0.95	0.93	0.96	0.92	6.0	6.7	4.9	9.8	1.9	2.1	1.7	2.5	8.5	6.6	8.5	6.2
	SI-6	5,737	0.0003	0.0021	0.92	0.89	0.93	0.92	9.9	10.6	9.6	9.9	2.4	2.5	2.4	2.3	9.2	7.4	8.1	9.2
	SI-7	7,674	0.0002	0.0012	0.95	0.94	0.96	0.93	6.1	5.8	5.7	8.5	1.9	2.0	1.7	2.4	8.3	4.9	8.3	5.6
	SI-8	11,567	0:0007	0.0011	0.96	0.94	0.97	0.93	5.2	5.7	4.5	7.9	1.8	2.0	1.6	2.3	6.0	5.6	6.0	5.1
C3 pH	pHF-1	7,080	0.0002	0.0012	0.98	0.97	0.98	0.97	0.002	0.003	0.002	0.003	0.037	0.043	0.035	0.041	0.121	0.121	0.118	0.117
	pHF-2	138,145	0.0001	0.0011	0.98	0.97	0.99	0.97	0.002	0.003	0.001	0.002	0.031	0.042	0.028	0.034	0.133	0.116	0.133	0.117
	pHF-3	10,103	0.0003	0.0012	0.97	0.97	0.98	0.96	0.002	0.003	0.002	0.003	0.038	0.046	0.035	0.041	0.127	0.122	0.127	0.121
C3 alum	pHI-1	22,844	0.0001	0.0004	0.99	0.98	0.99	0.99	20.1	18.8	21.7	14.5	3.4	3.4	3.5	2.9	14.3	11.2	14.3	8.4
	pHI-2	23,183	0.0001	0.0005	0.98	0.98	0.98	0.98	27.0	24.7	29.8	16.7	3.8	4.1	3.9	3.0	20.7	10.8	20.7	9.2
	pHI-3	18,231	0.0001	0.0006	0.98	0.98	0.98	0.98	24.4	26.0	25.0	19.5	3.4	3.8	3.3	3.3	17.8	11.9	17.8	10.5

Highlighted rows are best models.

All runs have the following in common
Topology - 5-layer backpropagation Ward Network
Activation Functions: Slab 1 - Linear <-1,1>, Slab 2 - Gaussian; Slab 3 - Tanh; Slab 4 - Gaussian complement; Slab 5 - Logistic
Number of Neurons in hidden layers - 5 per layer
Learning - Momentum/Random
Test set - 20% extracted randomly once - same set used for all runs
Production set - 15% extracted randomly once - same set used for all runs

2.5.5.1 Alum Clarifier ANN Model Results

For the alum clarifier, all the models look promising with pHF-1 and pHI-1 appearing to be the best. For predicting effluent pH, pHF-1 gave an R^2 value of 0.98 for all the patterns and 0.97 for the production set while for predicting alum dose, pHI-1 gave an impressive R^2 value of 0.99 for all the patterns as well as for the production set. The actual and predicted values of pH and alum dose are plotted on Figures 2-11 and 2-12, respectively.

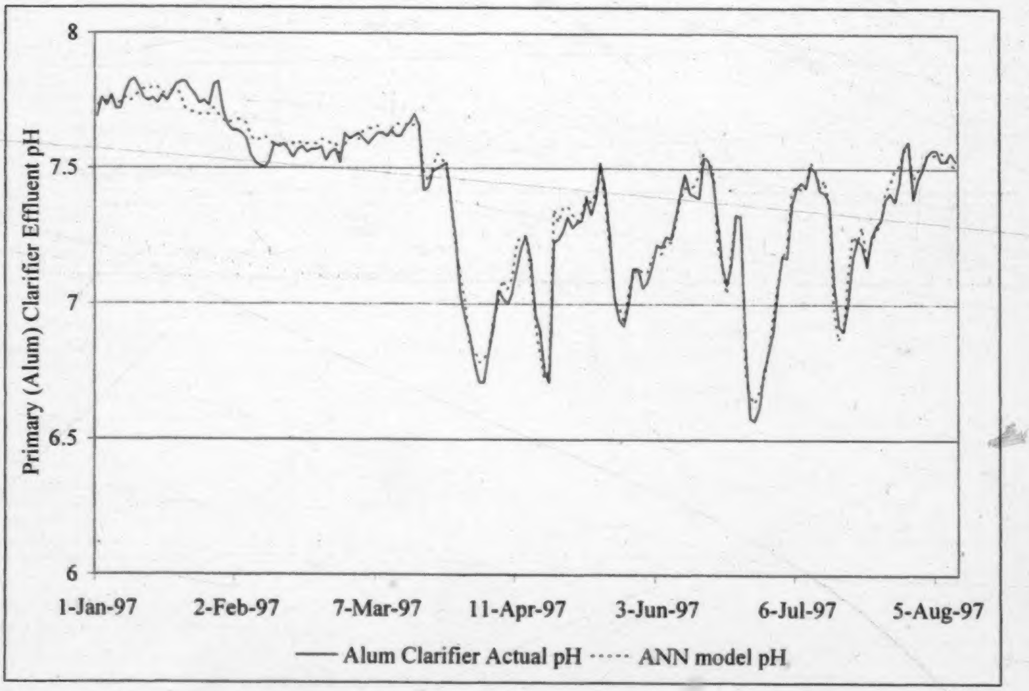


FIGURE 2-11 Alum clarifier effluent pH ANN

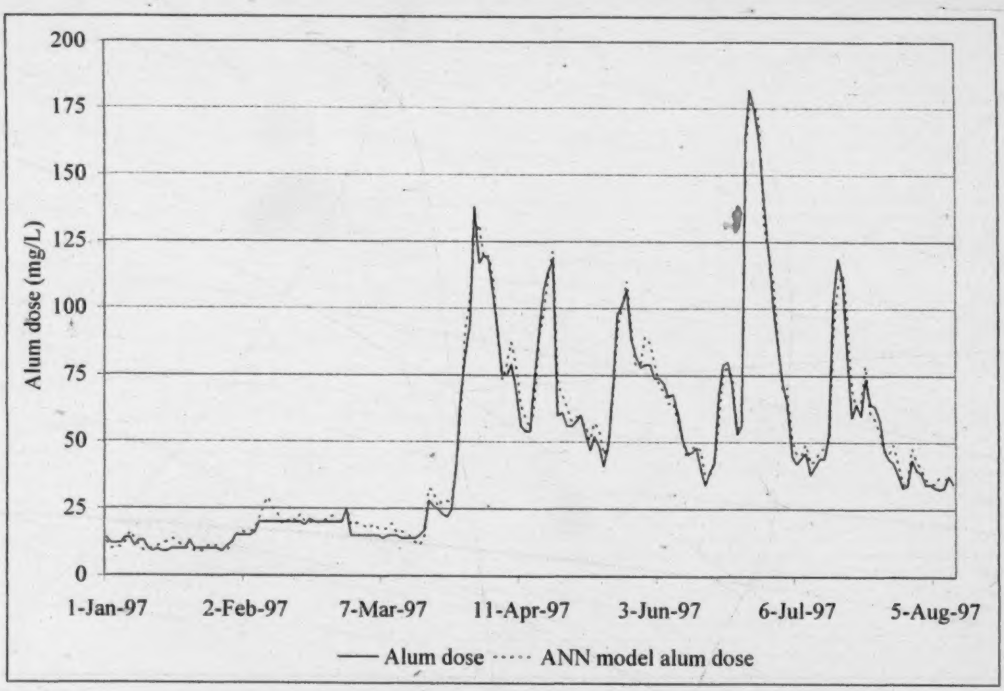


FIGURE 2-12 Alum clarifier influent alum dose ANN

2.5.5.2 Softening Clarifier ANN Model Results

For the softening clarifier, several models appear to predict the total hardness (forward model) and lime dose (inverse model) similarly. It appears that the best model for predicting hardness is SF-1. It had an R^2 value of 0.92 for all patterns and 0.84 for the production set. For predicting the lime dose, SI-1 stands out better having an R^2 value of 0.96 for all patterns and a 0.95 value for the production set. Since the discrepancy between actual and predicted values is greater for the forward model compared to the inverse model, particularly for the production set data, it indicates that the model still requires more optimization. The actual and predicted values of total hardness and lime dose are plotted on Figures 2-13 and 2-14, respectively.

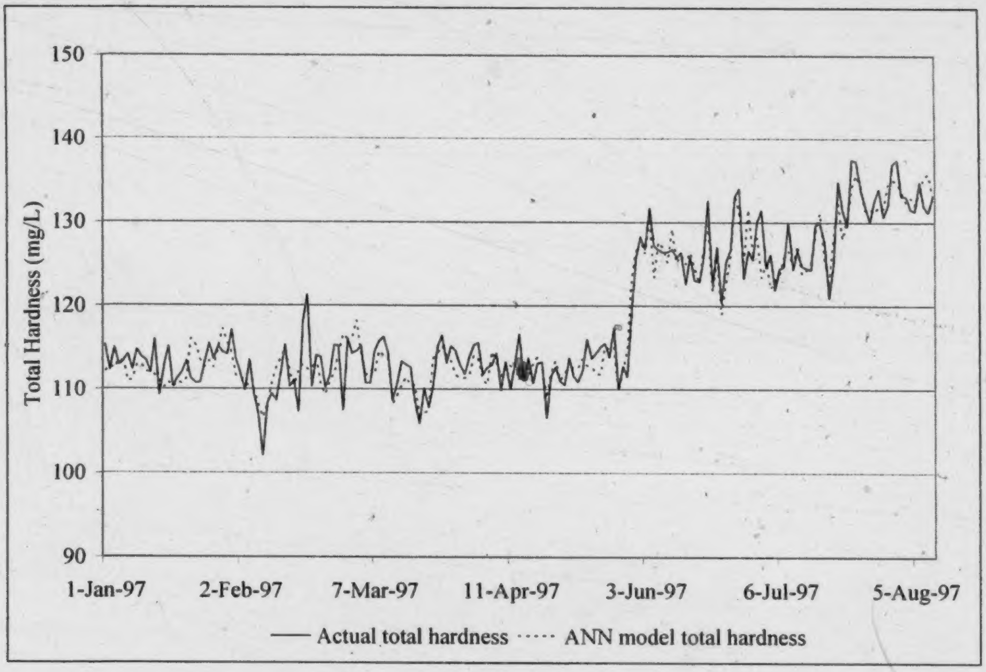


FIGURE 2-13 Softening clarifier effluent total hardness ANN

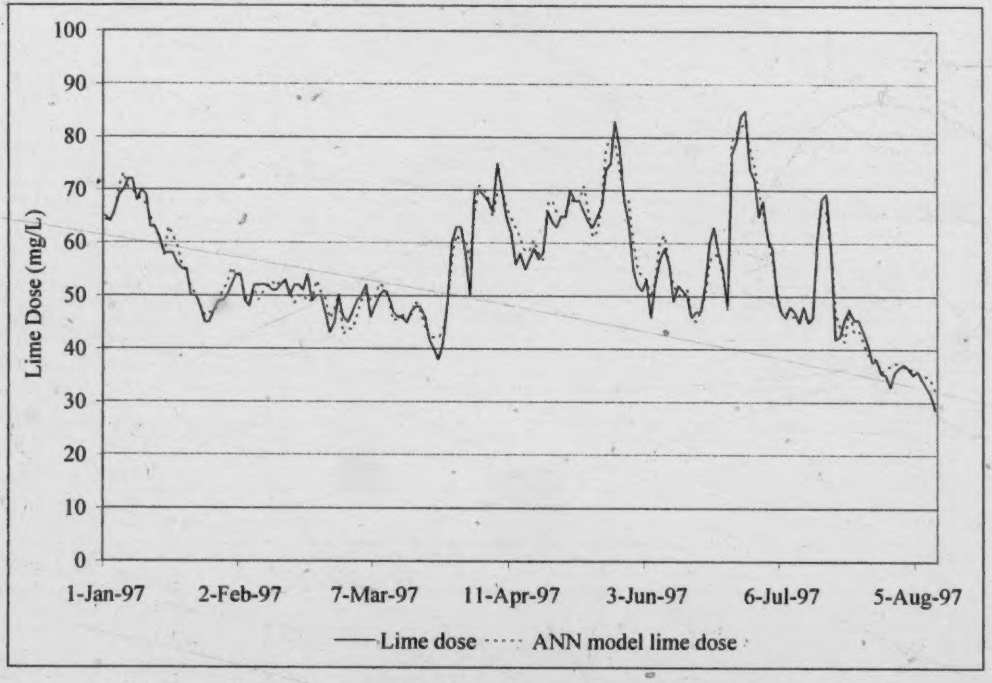


FIGURE 2-14 Softening clarifier influent lime dose ANN

2.5.5.3 Performance Comparison with the USEPA WTP Model

For comparison purposes, the USEPA WTP Model was used to make direct predictions for the softening clarifier effluent total hardness using the same plant actual data used to generate the ANN model. The model requires the user to "build" the plant electronically into the software and then enter appropriate data for the plant. In Appendix A, Figures A-1 to A-5 show examples of the various input forms that were filled out and the resulting output. The model was manually run for each data point used for developing the ANN model and the results are graphed in Figure 2-15. The USEPA WTP Model gave an R^2 value of 0.41 compared with the value of 0.92 achieved with the ANN model. It is apparent when reviewing all the results in Table A-2 in Appendix A that the USEPA Model has particularly large and seemingly unpredictable errors during times when the raw water quality is more challenging and higher values of alum dosages are being applied to the process. This was not the case with the ANN model predictions.

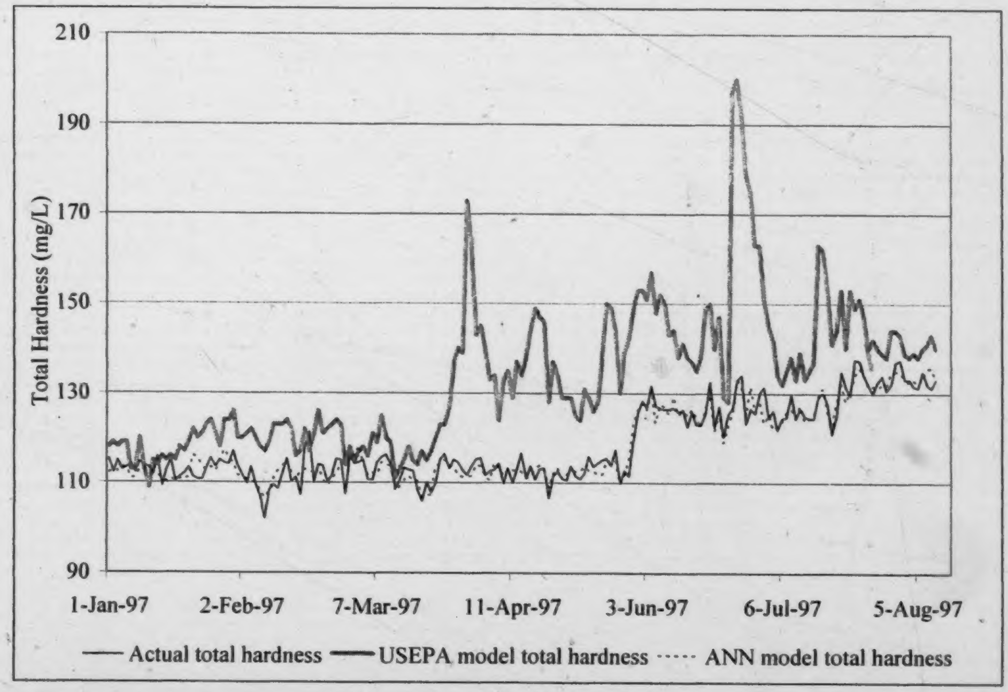


FIGURE 2-15 Performance comparison of softening clarifier effluent total hardness predictions using the USEPA WTP model and the ANN models

2.5.5.4 On-line Execution of ANN Models in Real-time

Once the ANN models for pH and lime softening were completed, run time models were created so that scenario testing could be conducted with either actual historical data (as was used to generate the graphs in the earlier sections), with new data from the plant in an off-line mode, or with new on-line plant data in real-time.

On-line execution of the ANN models requires porting of the run-time models to the SCADA system so that a two-way communication link can be formed between the model and the control system. The details of how this was accomplished are provided in the next chapter of this thesis. A partial set of the results from on-line testing on the Rossdale Plant #2 softening clarifier using the SCADA system is graphed in Figure 2-16. The results for both the forward model (predicting total hardness) and the inverse model (predicting lime dose) are shown in this figure.

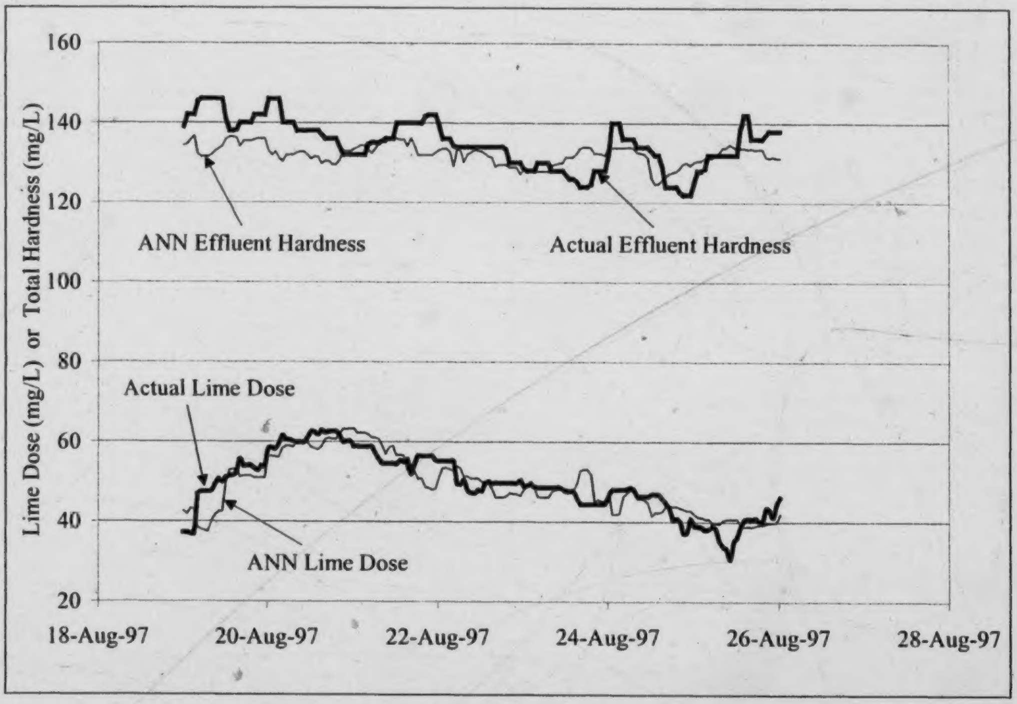


FIGURE 2-16 On-line performance of the softening clarifier ANN models

Although the ANN predicted lime dose during on-line testing was, except for a brief period, not used to automatically control the plant's lime feed system, porting of the ANN models to the SCADA system can certainly facilitate this. This will be described in more detail in the next chapter where advanced model-based control schemes utilizing both the forward and inverse models is proposed for improving the overall performance and control of the softening clarifier.

2.5.5.5 Error Sources and Analysis

In order to check the goodness of fit for the ANN models, a residual analysis of the data is also recommended (Zhang, 1996). A plot of the residuals versus actual effluent total hardness and actual lime dosages is shown in Figures 2-17 and 2-18, respectively.

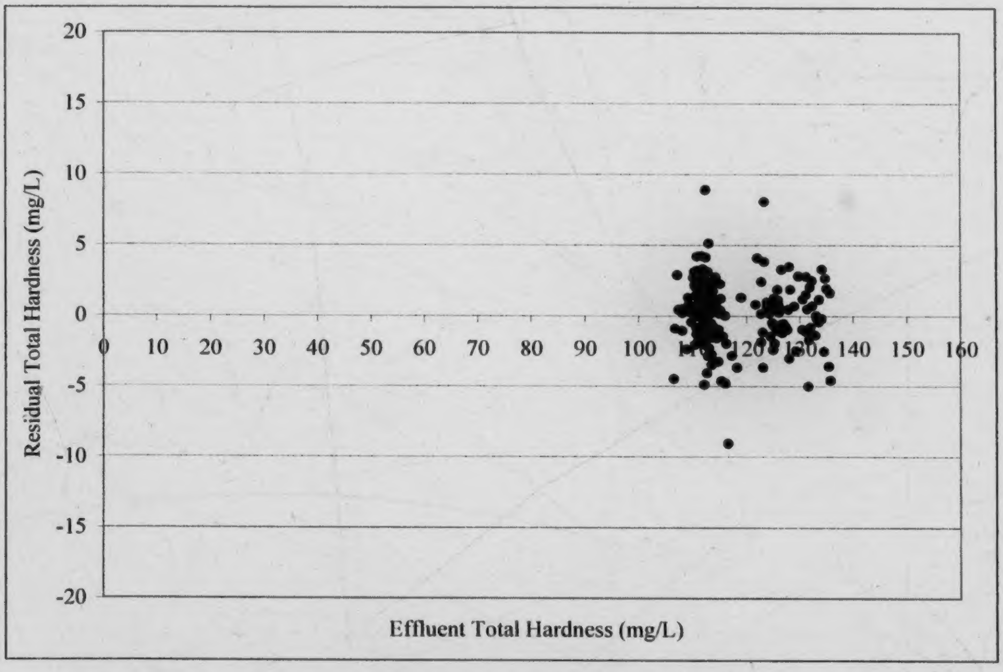


FIGURE 2-17 Residuals plot for the effluent total hardness ANN model

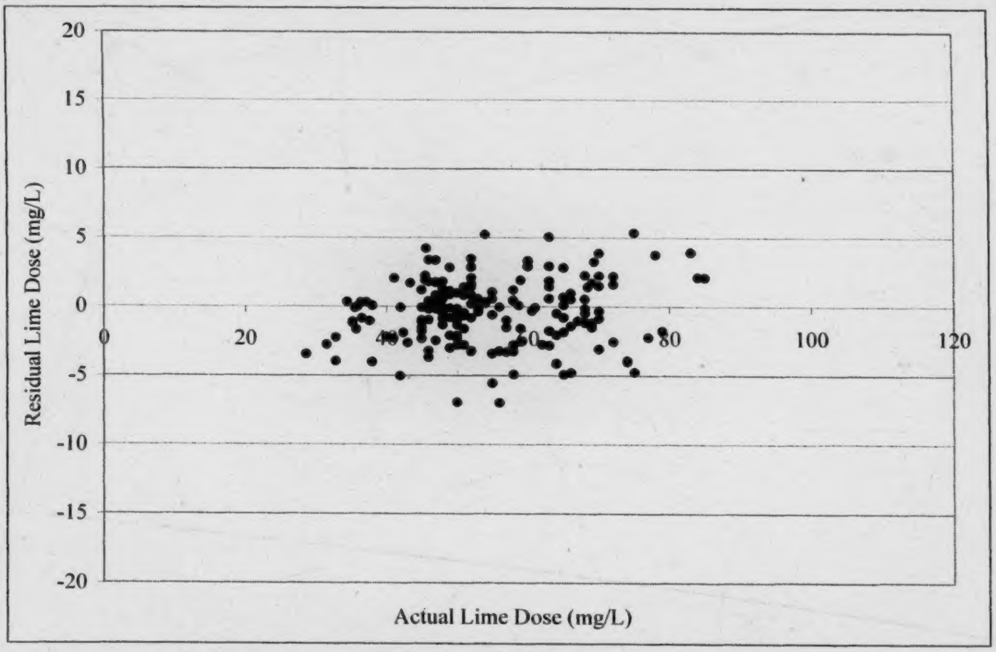


FIGURE 2-18 Residuals plot for the lime dose ANN model

In both instances, the mean of the residuals is close to zero (0.28 mg/L for effluent total hardness and –0.40 mg/L for lime dose) and the standard deviation is relatively low (2.30 mg/L and 2.29 mg/L, respectively). For both graphs, no special trends are discernable although densities of the residuals are different in some regions. For the total effluent hardness, there are two distinct locations where the density is high, one at about 112 mg/L and the second one at around 128 mg/L. This is due to the effluent target hardness value being increased by EPCOR Water Services in the latter part of the data set (see also Figure 2-8). For the lime dose residual graph, a higher density of residuals exists around 50 mg/L but this is due to more data being available in this region because the plant operates in this region more often. Overall, the models appear adequate based on residuals analysis.

Many sources of errors could have contributed towards the overall fit of the model to the actual process. Not using an important input such as clarifier solids concentration has been mentioned earlier. Other sources of errors could include such things as inaccurate and or imprecise lime feed rates. As shown in Table 2-6, the estimated lime feed accuracy is ± 10 to 20%. Compounded with this is the fact that the lime feed equipment at the Rossdale WTP tends to be a high maintenance item and on a weekly basis, the lime feeders are switched during which time the lime slakers get cleaned. During these events, the exact feed rates of lime are very questionable. Other errors can be related to lab analyses and data entry. Not using a large enough data set for the model may also be a contributing factor.

2.6 Discussion and Applicability of ANN Models

The ANN models developed in this work include the softening clarifier model and the alum clarifier pH model. The exercise of developing ANN models not only provides the model itself but also yielded significant information about the process that is being modeled. For example, an interesting feature that was observed on most of the models for the softening clarifier was the high contribution factors from alum and raw water flow. Initially, it was thought that the main effect of alum was a reduction of alkalinity available to the softening clarifier and a lowering of the pH in the alum clarifier effluent. Originally, when the alum clarifier effluent pH was not used as an input, the contribution of alum in the models was very significant as one would expect. However, after the pH was included as an input (this is the case for every model shown in this chapter), the contribution of the alum clarifier effluent pH was high but the contribution of alum stayed high as well. The plant operations staff have mentioned that the carry-over of alum from the alum clarifier to the softening clarifier affects the solids density, quality and consistency in the softening clarifier and the performance of the softening clarifier as a whole. The contribution of incoming raw water flow rate appears to be much higher than observed by the plant operator and this requires some more investigation. It is possible the amount of dead time in the clarifier could be an important input for the ANN model as it affects how much time it takes for a change at the inlet of a clarifier to be measured at the exit of the clarifier. Although not used as an input in this research, it is known that the amount of dead time in the clarifier varies with raw flow rate (an input that was used) and so in this situation, the contribution that raw water flow rate has made to the ANN model is more pronounced.

The ANN based models developed for the Rossdale Water Treatment Plant #2 were shown to be much more accurate than the USEPA WTP Modeling software. They could be useful at other plants with similar processes as the architecture and methodology developed in this research can be re-applied thereby greatly reducing the time required to develop the models. The ANN models would be updated using historical data specific to the other plant. The improved accuracy of the ANN model over the USEPA model provides clear advantages when it comes to the application of the models to improve plant operation and efficiency. Some of the areas that can benefit from accurate models include:

Chemical Budgeting

The softening ANN model predicts the lime dose required for a given set of input conditions. The model can be also utilized to predict gross amounts of lime required on a monthly or yearly basis depending on the type of data available. This would help with preparing chemical budgets. It also facilitates conducting "what if" scenarios such as what would be the expected amount of lime required and the impact on the budget if the target effluent total hardness were to be raised or lowered. Indeed, this type of scenario testing was the main reason that the ANN model was developed in this project. While the USEPA model was only able to predict total hardness to an accuracy of 15 mg/L on average with gross errors as high as 70 mg/L, the ANN model was within 0.5 mg/L on average with gross errors reaching only 9 mg/L. In addition, the average lime dose accuracy using the ANN model was less than 0.5 mg/L. Clearly, the ANN model is much more acceptable for use in predicting lime costs for budgeting purposes.

Plant Process Control

The ANN models that have been developed are particularly suited for making minute-by-minute predictions of lime requirements based on a target value of effluent total hardness. This capability can be applied in various ways to assist with plant operations. If the ANN models were to be integrated with the plant SCADA system, the prediction of lime dosages can occur in real-time. The operators can use this information to make adjustments to the lime feed rate (manual control) on an intermittent basis. If the ANN models were further integrated with the SCADA system such that they become part of an automatic control scheme such as feed-forward control, the lime dose predictions would be directly passed over to the lime feed system thereby providing automatic control of the softening clarifier. Several benefits can be realized with such an integration of ANN models with process control systems. Real-time automatic control ensures quick response to any changes occurring in the softening process thereby improving control and stability of the process. Improved control helps to narrow the operating boundaries of the process and improves consistency of water quality and operation, predictability of chemical usage, and sludge production. It can also save costs by ensuring that over-softening is reduced as is commonly done by operators who prefer to keep a buffer between target values and operating values for effluent hardness. Over-softening increases lime usage, sludge production, and pH adjustment chemicals all leading to higher costs.

Inferential Sensing and Alarming

The ANN based virtual pH meter developed in this project is not only useful as an input to the lime softening ANN model but is also useful for alarming. This is accomplished by comparing in real-time the value predicted by the virtual pH meter with a real on-line pH meter. If the difference between the two exceeds a preset value, an alarm can be generated notifying the operator. The operator would then investigate the cause which could be due to several things such as incorrect alum feed rates, erroneous readings from other on-line analyzers or bench tests, and failure of the actual pH meter itself. Corrective actions can then be made. Inferential sensing can therefore provide early warning of impending problems.

2.7 Conclusions

The results of this research indicate that ANN modeling can reasonably predict the performance of a full-scale drinking water treatment plant softening process. The fact that the production set R^2 values for the forward models are inferior compared to those for the inverse models warrants further investigation. It is probable that another input such as solids content in the clarifier (for which reliable data was not available) may be important. Still, the inverse model, which predicts lime dose, when considered by itself, is accurate and balanced between different data set patterns. The inverse model was of more interest from the outset since it gives a feed-forward value i.e. a lime dose value for a change in raw water conditions or alum dosages, and can be used by the plant operator for predicting lime dosages.

It was shown that the predictions for total hardness made by the USEPA WTP Modeling software were less than adequate. This was particularly true during times when the raw water quality was more challenging and was changing often and higher values of alum dosages were being applied to the process. This was not the case for the ANN based model predictions and thus the ANN model is much more accurate in this case.

The model for alum clarifier effluent pH (virtual pH meter) turned out to be very accurate in this research. It was developed in this study just to use as an input for the lime model when "what if" scenarios were conducted.

It was also shown that when the ANN models are integrated into the plant SCADA system such that the models interact with on-line systems, real-time predictions of lime dosages and effluent total hardness are possible. The performance of the ANN models in real-time turned out to be reasonable as well. Because of this, implementing an automated model-based control system for the softening clarifier is a distinct possibility. Prior to this endeavour however, a few additional checks and systems would be desirable. A more accurate model, perhaps developed with more historical data, additional on-line analyzers such as pH, total hardness, alkalinity, and a control strategy such as IMC (internal model control) or the more tunable MPC (model predictive control) (Shinskey, 1996) would make the automatic system more feasible. Other issues such as dead time introduced by the process and from discrete-type sampling analyzers would have to be resolved as well.

It should be mentioned that subsequent to this research, beginning in the year 2000, EPCOR Water Services stopped softening Edmonton's drinking water. The ANN models for the softening clarifier were no longer required although the ANN based virtual pH meter can still be used. The experience gained in developing ANN models is however being applied by EPCOR to other processes and other externally operated plants.

2.8 References

1. American Water Works Association. (1998). Water Treatment Plant Design, 3rd edition. McGraw-Hill, Inc., New York. 806 p.

2. Benefield, L.R., Judkins, J.F. and Weand B.L. (1982). Process Chemistry for Water and Wastewater Treatment. Prentice-Hall, Inc., Englewood Cliffs, N.J. 510 p.

3. Boger, Z., (1992). Application of Neural Networks to Water and Wastewater Treatment Plant Operation. ISA Transactions, 31, 1, 25-33.

4. Chapra, S. C. (1997). Surface Water-Quality Modeling. Prentice-Hall, Inc., McGraw-Hill, Inc., New York. 784 p.

5. Davies, M.L., Cornwell, D.A. (1998). Introduction to Environmental Engineering. WCB/McGraw-Hill, Boston. 919 p.

6. Droste, R.L. (1997). Theory and Practice of Water and Wastewater Treatment. John Wiley & Sons, Inc., New York. 800 p.

7. Hasham, F.A. (1998). Modelling of Urban Air Pollution in the Edmonton Strathcona Industrial Area using Artificial Neural Networks, M.Sc. Thesis, Department of Civil and Environmental Engineering, University of Alberta, Edmonton. 137 p.

8. Montgomery, J.Mm Consulting Engineers (1985). Water Treatment Principles and Design, 1st edition. John Wiley & Sons, Inc., New York. 696 p.

9. Patry, G.G. and Chapman, D. (1989). Dynamic Modeling and Expert Systems in Wastewater Engineering, 1st edition. Lewis Publishers, Inc., Chelsea, Michigan. 450 p.

10. Rodriguez, M.J., West, J.R., Powell, J. and Serodes, J.B. (1997). Application of two approaches to model chlorine residuals in Severn Trent Water LTD (STW) Distribution Systems. Water Science and Technology, 36, 5, 317-324.

11. Sawyer, C.N., McCarty, P.L. and Parkin, G.G. (1994). Chemistry for Environmental Engineering, 4th edition. McGraw-Hill, Inc., New York. 658 p.

12. Shariff, R. (1997). A Neural Network Model of the Rossdale WTP Softening Clarifier. Aqualta Inc., Edmonton, Alberta, Internal report.

13. Shinskey, F.G. (1996). Process Control Systems: application, design, and tuning, 4th edition. McGraw-Hill Co. Inc., New York. 439 p.

14. Snoeyink, V.L. and Jenkins, D. (1980). Water Chemistry. John Wiley & Sons, Inc., New York. 463 p.

15. Stanley, S.J., Baxter, C.W., Zhang, Q. and Shariff, R. (2000). Process Modeling and Control of Enhanced Coagulation. American Water Works Association Research Foundation Report No. 90784. Denver, Colo. 146 p.

16. Stergiou, C. and Siganos, D. (2001). Neural Networks, <www.doc.ic.ac.uk/~nd/surprise_96/journal/vol4/cs11/report.html>

17. U.S. Environmental Protection Agency (1993). Water Treatment Plant Model Software version 1.55, Cincinnati, Ohio.

18. Ward Systems Group Inc, (1996). NeuroShell 2 version 3 Neural Network Software, Frederick, MD.

19. Zhang, Q. and Stanley, S.J. (1997). Forecasting Raw-Water Quality Parameters for the North Saskatchewan River by Neural Network. Water Science and Technology, 31, 9, 2340-2350.

20. Zhang, Q. (1996). Artificial Neural Networks and their Application to Water Treatment, M.Sc. Thesis, Department of Civil and Environmental Engineering, University of Alberta, Edmonton. 145 p.

3.0 INTEGRATION OF ARTIFICIAL NEURAL NETWORKS WITH REAL-TIME PROCESS CONTROL SYSTEMS

3.1 Introduction

Virtually all water utilities are looking at improving the operation of their plants to keep control of costs and to meet stringent water quality regulations. Water quality improvements, increased productivity, and minimization of energy and chemical usage can be achieved through automation and optimization of plant processes. Automation entails eliminating intermediate components or steps in a process, especially those involving human intervention or decision-making, and replacing them with technologically more advanced ones (Schlenger et al, 1996).

Traditional control schemes are generally inadequate and advanced control techniques become necessary when automating certain water treatment processes such as turbidity, organics, or hardness removal in a clarification process. At the cornerstone of advanced control techniques is a model of the process being controlled, which can be developed using Artificial Neural Networks (ANN's). However, implementing advanced controls and reaping the benefits of automation first requires that effective integration of ANN based models with the plant real-time process control systems be done.

This chapter begins with an examination of advanced process control techniques and methods that were developed to integrate ANN based models with a real-time control system. It ends with an example of an advanced control system running in real-time for the softening process at the Rossdale Water Treatment Plant in Edmonton, Alberta, Canada.

3.2 Artificial Neural Network Models in Process Control

Models of processes support most modern control approaches and depending on the form of model developed, different types of controllers can be synthesized. Using models for systems or processes reduces the need for real experimentation and facilitates the achievement of many different purposes at reduced cost, risk and time (Willis and Tham, 1994).

In process control, models can be useful for simulating processes to help train operators and for conducting "what-if" scenarios in an off-line manner prior to making adjustments to the process. They are also useful for continuous on-line monitoring of the process by making predictions of what will occur in the near future, for developing virtual instrumentation (also known as inferential sensing) or validating existing ones, and to implement advanced controls for automation and cost control.

3.2.1 Conventional Process Control Schemes

The most common type of controller utilized to implement conventional process control schemes are known as the Proportional-Integral-Derivative or PID controllers. General equations for PID type controllers are shown in Equations 3.1 and 3.2 (VanDoren, 1998) although many variations including proprietary versions exist.

In theory

$$CO(t) = P \bullet e(t) \quad + \quad I \bullet \left(\int e(t)dt \right) \quad + \quad D \bullet \left(d/dt\, e(t) \right) \qquad (3.1)$$

In practice

$$CO(t) = P \bullet \Big[e(t) \quad + \quad 1/T_I \bullet \left(\int e(t)dt \right) \quad - \quad T_D \bullet \left(d/dt\, PV(t) \right) \Big] \qquad (3.2)$$

where:

CO(t) = Controller output at time t.

$PV(t)$ = Process variable value at time t.

$e(t)$ = Error value at time t = $SP(t) - PV(t)$.

where: $SP(t)$ = Setpoint value at time t.

P = Proportional term tuning constant.

$I, 1/T_I$ = Integral term tuning constant.

D, T_D = Derivative term tuning constant.

The output of a PID controller is determined by observing the error between a desired set-point and a measurement of the process variable. The error can be generated by an operator changing the value of the set-point intentionally, or when the value of the process variable changes due to load changes. In either case, the PID controller compensates for the error by making changes to its output to drive the process back towards the desired set-point. The value of a PID controller output (corrective action) comprises the addition of the current error, the integral of the error over a recent time period, and the current derivative of the error signal each multiplied by a corresponding tuning constant.

On the average, PID controllers account for 80% of all feed-back controllers installed in plants and are well suited for linear processes that have little or no time delays (Willis and Tham, 1994). Most control loops in a process plant can be classified into five categories: flow, pressure, liquid level, product quality, and temperature (Shinskey, 1996). Thus, many of these control loops are controlled with PID controllers. Examples in water treatment plants include: water and chemical flow control, distribution pressure control, tank and reservoir level control, chlorine and pH residual control, and sometimes raw water temperature control.

However, PID controllers are not suitable for all control loops, particularly those that are related to the category *product quality* which is typically the most important and difficult loop to tune in a process plant (Shinskey, 1996). Water treatment processes tend to be non-linear and can change with time and if a PID controller is used, the tuning parameters would require frequent changes. In addition, water treatment processes such as clarification have large time delays (also known as transportation delay or dead-time) which make PID controllers less suitable for control. A third problem that is difficult for conventional control schemes to handle is related to multivariable control (i.e. when more than one process variable requires regulation). In conventional control schemes, multiple PID loops would be developed, each designed to regulate just one process variable. When the regulation of one process variable affects another process variable, loop interaction is said to exist and unless the PID loops are de-tuned or made less sensitive (which leads to sluggish performance), instability may occur.

Therefore, using conventional control schemes for control of water treatment plant processes such as clarification can lead to poor performance. Advanced control schemes are designed to handle many of the difficulties mentioned and are discussed in the next section.

3.2.2 Advanced Process Control Schemes

Unlike conventional control schemes, advanced process control schemes are designed to better handle non-linear process dynamics and time-delays. They can be made adaptive or self-correcting and many incorporate models to predict set-points. In an advanced control strategy known as Model Based Control (MBC), a process model is explicitly used to predict future process behaviour. The same model is also implicitly used (essentially inverted) to calculate the control action necessary to satisfy a set-point.

3.2.2.1 Forward and Inverse Modeling

The two types of models used in MBC as described above are known as a forward model (otherwise known as a process model) and an inverse model. Forward modeling involves mapping the forward dynamics of a process and therefore the output is a prediction of the future value of the process variable. Similarly, inverse modeling involves mapping the inverse dynamics of a process and the output is a prediction of the value of the control variable that will be required to meet a target value of the process variable. Figure 3-1 further illustrates the two types of models.

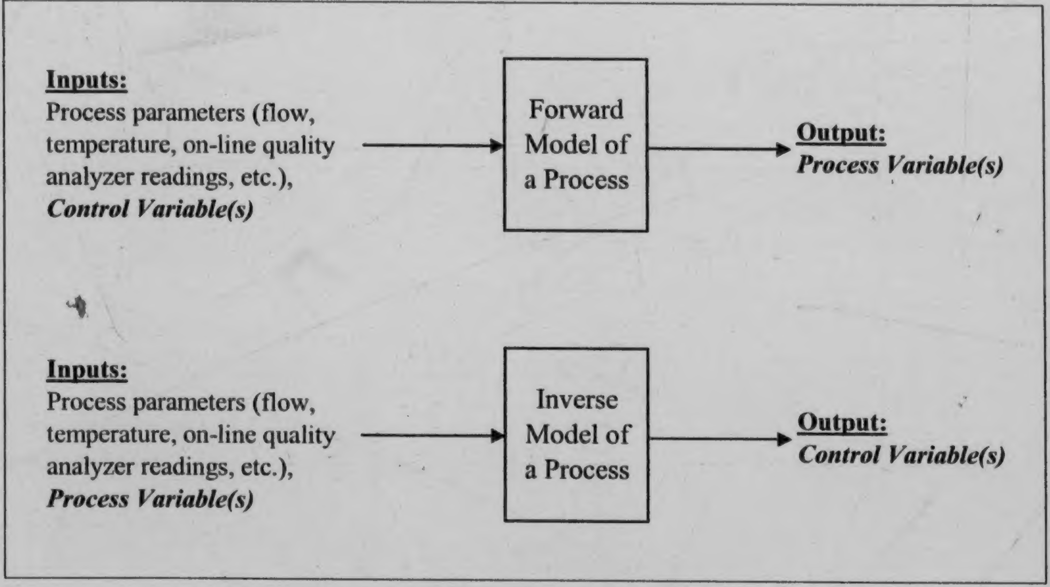

Inputs:
Process parameters (flow, temperature, on-line quality analyzer readings, etc.), Control Variable(s)
Forward Model of a Process
Output: Process Variable(s)
Inputs:
Process parameters (flow, temperature, on-line quality analyzer readings, etc.), Process Variable(s)
Inverse Model of a Process
Output: Control Variable(s)

FIGURE 3-1 Forward and inverse models

3.2.2.2 Direct and Indirect Control Methods

In process control applications, forward and inverse models can be incorporated into controllers either indirectly or directly. Forward models are used for the indirect method. Since a forward model does not directly predict the value of the control variable, an iterative method is required to arrive at a value for the control variable to meet a process variable target set-point. In the direct method, the inverse model is utilized. Since an inverse model directly predicts the value of the control variable required to meet a process variable target set-point, it can be incorporated directly into a controller, usually as a feed-forward control scheme.

According to Psichogios (1991) there are advantages and disadvantages of both direct and indirect control methods. The main advantage of direct control is the ability to quickly determine the control action (variable). However, not all process models can be rigorously inverted. For example, in a given process, there may be more than one value of the control variable that can yield the same value of the process variable. Furthermore, when the ANN modeling technique is used to map the inverse dynamics of a process, it can result in incorrect learning if the underlying process is not invertible, and therefore may not necessarily provide the same results as that predicted by inverting the forward process model. An alternative method then is to invert the forward process model on-line. As mentioned earlier, this requires an iterative approach at arriving at a solution for the control variable. It also takes more processing time and may give convergence problems. However, this method offers more flexibility including the ability to incorporate constraints more easily and in general gives better performance (Psichogios, 1991).

3.2.2.3 Model Based Control Schemes

The models required for implementing MBC schemes can be particularly difficult and expensive if not impossible to develop if traditional methods of modeling such as mechanistic or experimental are used. The ANN modeling technique on the other hand can be used to quickly develop both forward and inverse models provided that historical data regarding the performance of the process is available. Many modern water treatment plants collect and store a large amount of information from on-line sensors. The ANN technique therefore opens up the possibility of testing MBC schemes for water treatment processes without a large initial investment of capital.

In the following discussion, two control schemes are described to illustrate how MBC can provide automatic process control. The first scheme is known as the Ideal Model Based Control Scheme and the second scheme, which is much more complex, is called the Internal Model Control Scheme.

Ideal Model Based Control (MBC) Scheme

An ideal MBC scheme is shown in Figure 3-2 where an inverse model is incorporated in a feed-forward fashion. The inverse model receives the desired set-point of the process variable and along with other relevant model inputs, calculates an appropriate value of the control variable which is then passed over to the front (feed-forward) of the plant.

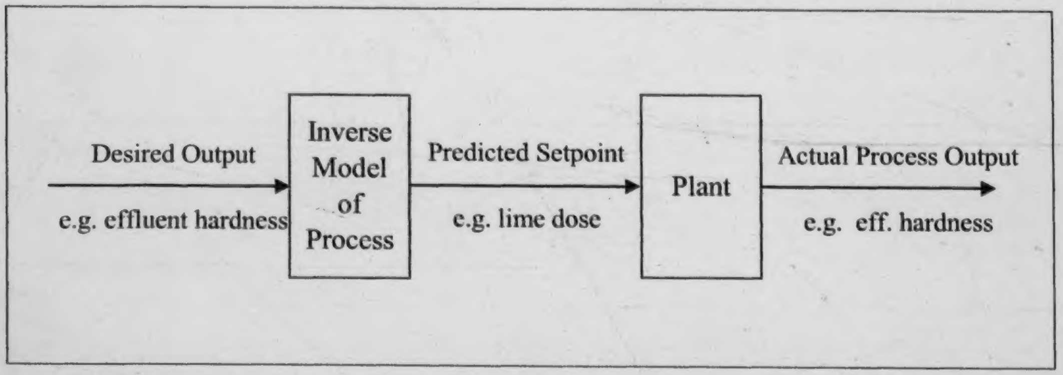


FIGURE 3-2 Ideal model-based (feed-forward) control scheme for a softening clarifier

Assuming that the inverse model is very accurate, the output of the process will always match the desired output. That is to say that model-based control has the potential to provide perfect control. This is not the case with traditional PID feed-back control where control action only occurs when there is an error between the process and control variable. In reality though, perfect control with MBC is very difficult to achieve due to such things as inaccuracies in sensor readings that are used as inputs to the model and errors in the model itself. Therefore, modern control techniques are being developed to address this issue. One such technique known as the Internal Model Control (IMC) scheme is described in the next section.

Internal Model Control (IMC) Scheme

An important subject in modern control engineering is that of robust control or robustness of a controller. Simply put, it is the ability of a system to continue performing satisfactorily despite variations in plant dynamics. Morari and Zafirious (1989) define a controller to be "robust" if it will maintain stability while at the same time achieve a specified performance over the desired operating conditions.

Robust control therefore is typically formulated as a compromise between achieving performance and ensuring stability under assumed process uncertainties. The compromise between the two is necessary because each can affect the other in a detrimental manner. Willis and Tham (1994) describe this compromise as follows: in order to achieve performance objectives, a sensitive controller is required. However, a very sensitive controller will also be sensitive to process uncertainties which can create stability problems. An insensitive controller on the other hand will have poorer performance with sluggish response. Shinskey (1996) further describes robustness as follows: in general, the higher the performance of a controller, the lower the robustness. However, the reverse is not necessarily true - just because a loop has low robustness does not mean that the controller performance is necessarily high.

In water treatment processes, process uncertainties, non-linearities, and large dead-times make it more difficult to design robust controllers. Modeling of the water treatment process helps but a control scheme that is designed to impart a higher level of robustness is also required.

The design of robust controllers involves what is called the "internal model" principle which states that unless a control scheme contains a description (model) of the controlled process (either implicitly or explicitly), then either the performance or stability criterion, or both, will not be achieved (Willis and Tham, 1994). Based on this principle, the Internal Model Control design shown in Figure 3-3 is a control scheme that is designed to impart robustness and theoretically, perfect control.

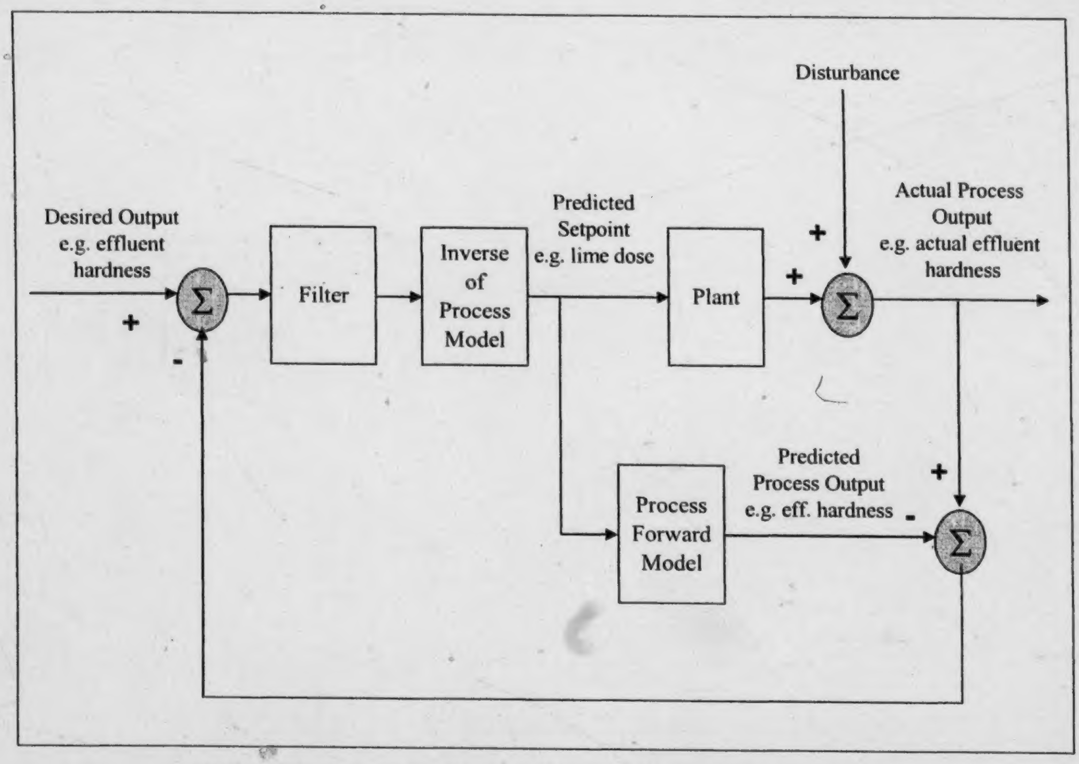

Disturbance
Desired Output e.g. effluent hardness
+
-
Filter
Inverse of Process Model
Predicted Setpoint e.g. lime dose
Plant
+
+
Actual Process Output e.g. actual effluent hardness
Process Forward Model
Predicted Process Output e.g. eff. hardness
+
-

FIGURE 3-3 Example of an Internal Model Control scheme

Both forward and inverse models are integrated in the IMC control scheme. As was done in the ideal model based control scheme (Figure 3-2), the inverse model is used to predict the value of the control variable. In the IMC scheme, this control variable is not only passed to the plant but also to the forward process model, which in turn makes a prediction of the process variable. This value is compared with the actual process variable value from the plant and the difference is fed back to the beginning of the control scheme where it in turn is subtracted from the desired set-point. This value then forms the new set-point for the inverse model. The function of the filter is to moderate excessive control action and to achieve a desired degree of robustness (Stanley et al, 2000). The internal model principle which the IMC scheme is based upon is a very powerful concept and is the essence of MBC and all model based controllers can be designed within its framework (Willis and Tham, 1994).

3.2.2.4 Process Optimization and Plant-Wide Control

The benefits gained from modeling of processes and subsequently implementing advanced controls to automate the processes can be extended plant-wide by optimizing overall plant operations. Plant-wide control systems incorporate an optimizer (see Figure 3-4) which, through the use of an overall plant model, minimizes raw material usage and maximizes profits. In achieving this, the optimizer takes into consideration the costs and overall quality targets before generating set-points for individual process control systems that are not necessarily optimum for them individually but optimum for the overall plant.

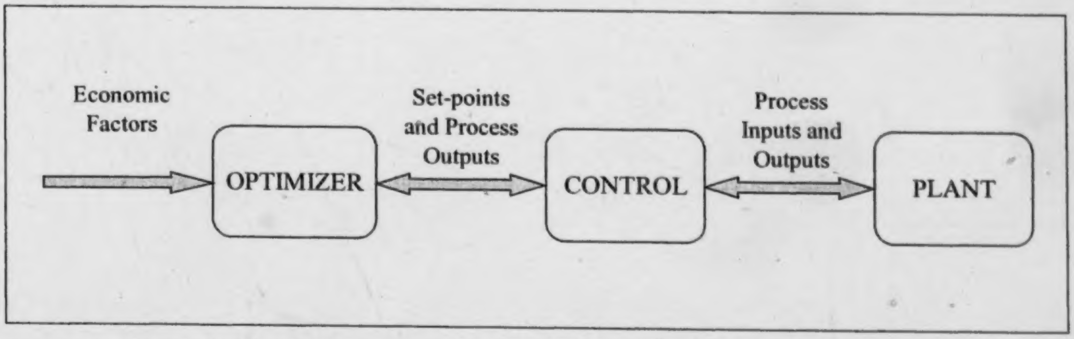


FIGURE 3-4 Structure of an optimization scheme (after Willis and Tham, 1994)

An example of how plant-wide control can be useful is shown in Figure 3-5. The figure depicts roughly the E.L. Smith WTP in Edmonton, which has clarification and filtration stages and various chemicals to treat the water. If only individual models for the clarification and filtration stages were developed, each stage could be optimized individually. However, it is known that the performance of the filtration stage is greatly dependent on the performance of the clarification stage and the chemicals applied prior to and after the clarification stage. The lowest clarifier effluent turbidity does not always necessarily mean that best filtration performance will occur or that the lowest chemical and filter back-washing costs will be incurred. To optimize the operation of the overall plant while attempting to minimize costs, an overall plant model can be developed that links both models and/or processes together. The overall plant model would then be used by an optimizer which would generate the operating ranges or set-points for such things as the clarifier effluent turbidity. The various control systems would be directed by the optimizer to follow the operating ranges which again, may not be optimum for an individual process unit but would be optimized to meet both the overall business and local plant operating objectives.

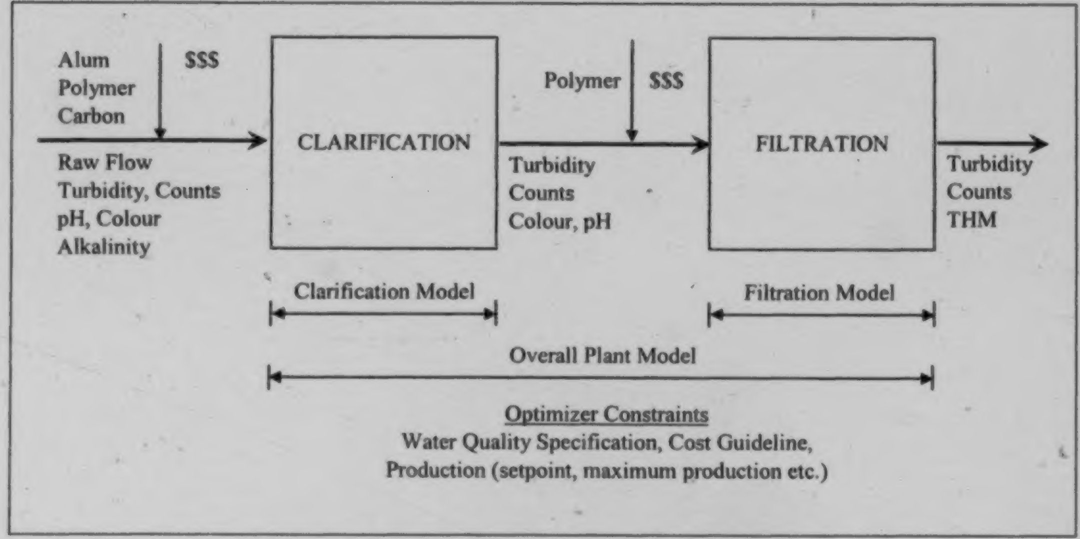

Alum
Polymer
Carbon
$$$
Raw Flow
Turbidity, Counts
pH, Colour
Alkalinity
CLARIFICATION
Polymer
$$$
Turbidity
Counts
Colour, pH
FILTRATION
Turbidity
Counts
THM
Clarification Model
Filtration Model
Overall Plant Model
Optimizer Constraints
Water Quality Specification, Cost Guideline,
Production (setpoint, maximum production etc.)

FIGURE 3-5 Overall plant control strategy example

3.2.3 Inferential Sensing

In the previous discussion on model-based control schemes, it was assumed that all the required data for model development and for execution of the control schemes in real-time was available and reasonably accurate. In practice, more often than not, this may not be the case due to a few major reasons:

Lack of On-line Instrumentation – due to affordability (initial purchase cost and subsequent ongoing costs of maintenance), or because an on-line analyzer for the parameter in question does not exist. This can lead to reliance on infrequent and irregularly conducted laboratory tests and long delays in analysis resulting in difficulties with implementing process control.

Reliability of On-line Instrumentation – due to drifts, fouling, reduced maintenance frequency to save costs, sampling difficulties, and sampling delays.

Even if a required on-line instrument is available and is reliable enough for use when automatic control is active, an early estimate of what its reading might be may be important when what-if scenarios or simulation studies are being conducted. A case study where an early estimate of a softening clarifier influent pH reading was required is described later on in this section.

Through a methodology known as inferential measurement, the equivalent of an on-line instrument reading can be predicted. This is done by developing a relationship between a primary variable (the "missing" on-line instrument) and secondary variables (readily available on-line readings that affect the primary measurement). The relationship between the primary and secondary variables can be developed through modeling. Any modeling paradigm including first principles models can be used although development of data based (time series, ANN, genetic programming) inferential measurement can be less difficult and less time consuming (Tham, 2000). For non-linear types of inferential measurements, the use of ANN's are particularly suited and are sometimes known as "neural analyzers" (Deshpande, 1997). Other phrases that are used to describe inferential measurement include: inferential sensor, virtual sensor, virtual instrument, and soft-sensor (software sensor).

Once an inferential sensor has been developed and proven to be accurate in an on-line situation, it can be used for control applications including actually becoming part of an actively running control loop. Figure 3-6 illustrates how inferential measurement can be used as a "soft-sensor" to quickly estimate the value of the primary output variable using secondary outputs and then pass those values as delay free feed-back.

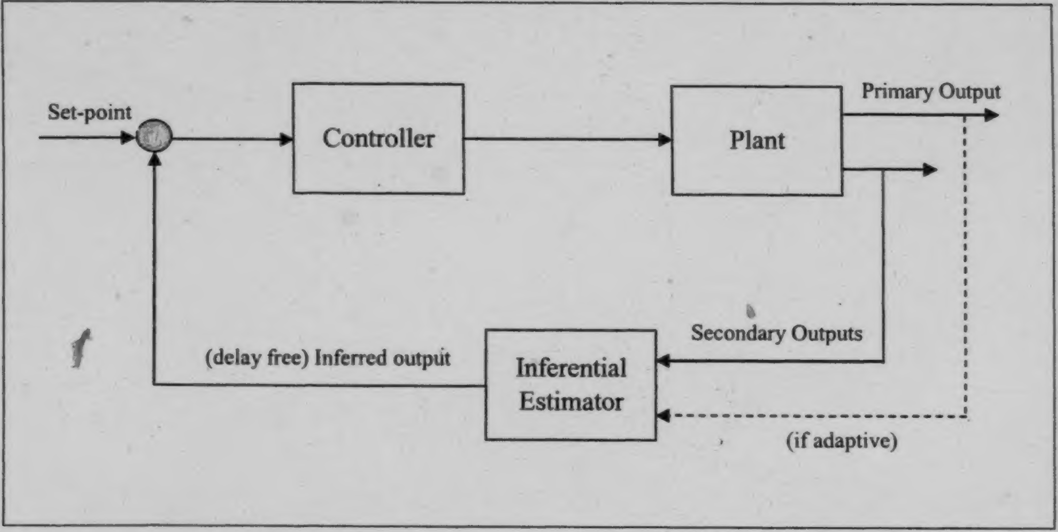

Set-point
Controller
Plant
Primary Output
Secondary Outputs
(delay free) Inferred output
Inferential Estimator
(if adaptive)

FIGURE 3-6 Using a "soft-sensor" as part of a control loop (after Tham, 2000)

A practical example of where an inferential sensor can be useful is illustrated in Figure 3-7. An ANN model for the softening process at the Rossdale Water Treatment Plant was developed. All the important inputs to the model are those measured at the influent to the alum and the influent to the lime clarifiers. The overall ANN model for the softening process is shown at the bottom of Figure 3-7. Of particular interest is the input called "pH lime influent". Since an on-line pH meter to measure this input was not installed at the plant, its value had to be estimated in real-time. Using operator lab test data for pH lime influent, a virtual or soft-sensor was developed using ANN as shown in the middle portion of Figure 3-7. To predict the lime dose requirements for the softening process, the virtual pH meter ANN model is executed first and its output is fed directly to the lime dose ANN model.

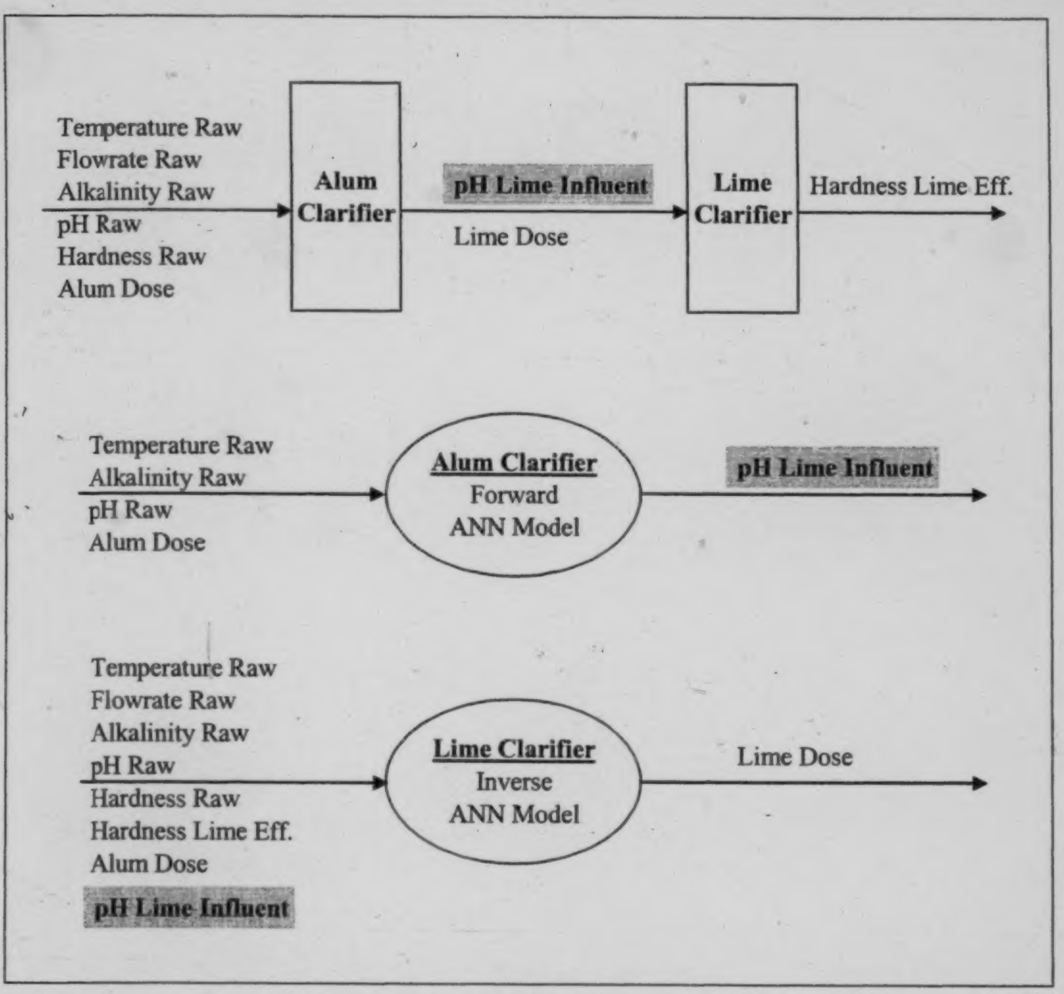

Temperature Raw
Flowrate Raw
Alkalinity Raw
pH Raw
Hardness Raw
Alum Dose
Alum Clarifier
pH Lime Influent
Lime Dose
Lime Clarifier
Hardness Lime Eff.
Temperature Raw
Alkalinity Raw
pH Raw
Alum Dose
Alum Clarifier
Forward
ANN Model
pH Lime Influent
Temperature Raw
Flowrate Raw
Alkalinity Raw
pH Raw
Hardness Raw
Hardness Lime Eff.
Alum Dose
pH Lime Influent
Lime Clarifier
Inverse
ANN Model
Lime Dose

FIGURE 3-7 Modeling the lime softening clarifier and virtual pH meter (after Stanley et al, 2001)

It should be mentioned that even if an on-line pH meter had been available for the example in Figure 3-7, a virtual pH meter would still be necessary to conduct simulation tests for the lime softening ANN model. Although pH lime influent is an input to the overall softening model, its value is dependent on other independent inputs such as temperature, alkalinity, raw water pH, and alum dose. Therefore, during simulation, the value of pH lime influent must be determined after the other input values have been chosen.

Inferential sensing can also be useful for validating existing on-line analyzers. Basically, the readings from both the on-line and inferential sensors are compared in real-time and when the difference between the two exceeds a pre-set value, an alarm would be generated to alert the plant operator. An investigation can then carried out to determine the cause. Validation of analyzers in real-time not only provides early detection of an impending problem but can also assist with controlling the costs of maintenance of the instrument by ensuring that the analyzers do not get serviced excessively even if they are performing well.

3.2.4 Issues with On-line ANN Execution

One fact that may be evident from the previous topics in this chapter is that all control schemes require data to make them function properly. Therefore, data must be carefully checked during model building and during model execution. These and other issues that are important when ANN models are used on-line are discussed further below.

Sampling Frequency

When an ANN model is developed, the data used may have a sampling frequency and smoothing or averaging factors that are quite different from what the developed model is subjected to during on-line execution. For example, ANN models that were developed for the Rossdale WTP softening process (and as well, models for other processes developed by other researchers at the University of Alberta, Department of Civil and Environmental Engineering) used daily averaged values. During on-line testing, the models were executed essentially in real-time at about a one-minute frequency. In the case of the softening process ANN model, the accuracy of predictions were about the same as during model development but some smoothing of the output (lime dose) values was required to reduce excessive changes of the lime feed rates. When a model is executed at a faster or slower frequency than at the development stage, an accuracy check should be conducted to confirm its validity prior to using it for automatic control.

Data Conditioning

When real-time data from on-line instrumentation is fed to the ANN model, it is important to condition the data where necessary. Conditioning could mean a reduction of spikes and noise with filters, identification and removal of suspicious data points, and detection of analyzer failures through built-in alarms generated by the analyzer itself or through an inferential sensor operating in parallel. The automatic control system should be programmed to deactivate and generate an alarm when failures occur so as not to negatively affect the process.

On-line Analyzer Performance

The reliability and accuracy of data from on-line analyzers used by the control system depends to a large degree on the commitment of resources to a quality assurance program (Shariff et al, 2001). Most on-line analyzers used in the water treatment industry, for example, require regular maintenance to keep them functioning well. For critical locations, duplicate or even triplicate analyzers may be warranted to ensure that accurate readings are being used by the control system.

Out of Domain Inputs

During ANN model development, the data set provided to the model forms the domain within which subsequent predictions by the model are considered valid. As long as the values of each of the input parameters fall within the range of values on which the models were developed, the ANN model will interpolate well and accurate predictions can be made (Baxter et al, 2001). Predictions made outside the domain can be inaccurate and therefore must be detected on-line so that the control system is able to react by deactivating its output and alerting the plant operator of the situation. To detect an out-of-domain condition, a classification technique such as a Kohonen classifier can be employed (Stanley et al, 2001). Briefly, the method is as follows: before the input set is read by the ANN models, it is first passed through a Kohonen classifier ANN model which categorizes the new inputs into one of several known categories. If the input set does not fit any of the known categories, the input set is flagged as an out-of-domain condition and an alarm occurs which prevents the process models from outputting their values to the rest of the control system.

Model Accuracy with Time

Once an ANN model has been developed from a historical data set, it can be used to make accurate predictions as long as no significant changes occur that place the ANN model in an out-of-domain predicament. Significant changes to the raw material, quality of the incoming feed to the process, the process itself, and other environmental factors could all affect model accuracy.

What is important for on-line implementation is to be able to actively detect that model drift is occurring. One method to detect the drift is described by Bhat and McAvoy (1990) which used two ANN models running side-by-side. Initially, both models are exactly the same as they are trained on the same historical data set. Then one model is frozen and is used on-line while the second model is re-trained as soon as enough new historical data is acquired. Both models make predictions and the two are compared frequently. In addition, the accuracy of the re-trained model is also monitored as it could decline should significant process changes occur such as the use of a new chemical. In this case, the model may need to incorporate new inputs prior to re-training. If the accuracy of re-trained model is satisfactory and is significantly superior to the frozen model, the frozen model is removed and replaced with the re-trained model and the process is then repeated.

People Issues

As with any new technology implementation, acceptance by stake-holders is critical to ensure a favourable result. Since ANN models are black-box type models (Zhang, 1996), it is even more difficult to convince users of its validity as there are no equations to show

how a solution is arrived at. It is therefore imperative to work closely with users and show them how and why this technology works followed by examples showing it working. It has been the author's experience that operators tend to accept new ideas if one can show that it works and will help them run the plant better.

3.3 ANN Model Integration with Real-time Control Systems

A natural follow up to the development of process models and their inclusion in advanced control scheme designs is integration with plant control systems. Plant control systems operate in real-time to monitor, control, collect data, generate alarms, perform safety protocols, and execute control commands from operators or automatically through a control program. Integrating ANN models with a real-time control system either as a standalone system or via advanced control schemes can greatly extend the benefits of the ANN modeling technique. This is because the system would be able to continuously predict optimum set-points and if automated, optimize process parameters, costs, and attain other plant objectives.

For ANN models to work effectively within a real-time control system, various systems are required. These requirements are discussed further in the ensuing section. Following this is an illustration of how a softening clarifier lime dose prediction ANN model (developed in chapter 2 of this thesis) was integrated with EPCOR's Rossdale WTP control system to run in real-time using a feed-forward control scheme.

3.3.1 Integration Requirements

The integration of ANN models with real-time control systems requires that several systems such as on-line analyzers, computer hardware and software, and communication network systems work together in harmony. Furthermore, to make the integration more useful, the needs of the different users within a company should be incorporated at the design phase. For example, plant operations personnel would have needs for both on-line and off-line models for process control, simulation and training, virtual analyzers, cost control and optimization. Other users' needs may include scenario testing and longer term forecasting for such items as water demands and chemical usage. Thus, information needs to flow to and from the different users and this can affect how the various systems mentioned earlier are integrated. Once implemented, user training of the ANN system is a critical requirement to the overall success of the system.

In addition to having appropriate systems, procedures and protocols such as those identified earlier in this chapter, there are two key additional items that facilitate the integration of ANN's in a real-time control system: SCADA systems and ANN Interfaces.

3.3.1.1 SCADA Systems

A central part of many control systems in modern plants is the Supervisory Control and Data Acquisition (SCADA) system. SCADA systems really describe two separate functions – supervisory control is the remote control of devices such as pumps and valves while data acquisition is the acquisition of data such as flow, pressure, and turbidity from remote sensors (Gotoh et al, 1993).

SCADA systems typically run continuously and in real-time and are a very useful tool for operating plants as they can be used to monitor and control equipment, record data, rapidly identify problems, alert operators through alarms, and automatically activate shutdown or startup sequences (Shariff et al, 2002). The vast amount of data stored by the SCADA system is not only useful for preparing reports and to assist in troubleshooting, but also for studying the performance of plant processes, in developing models, and to help optimize costs and quality.

The various components that make up a SCADA system include communication networks, computer systems including hardware and software, Programmable Logic Controllers (PLC's), and on-line instruments. An example layout of a SCADA system for a water treatment plant illustrating these components is shown in Figure 3-8.

8

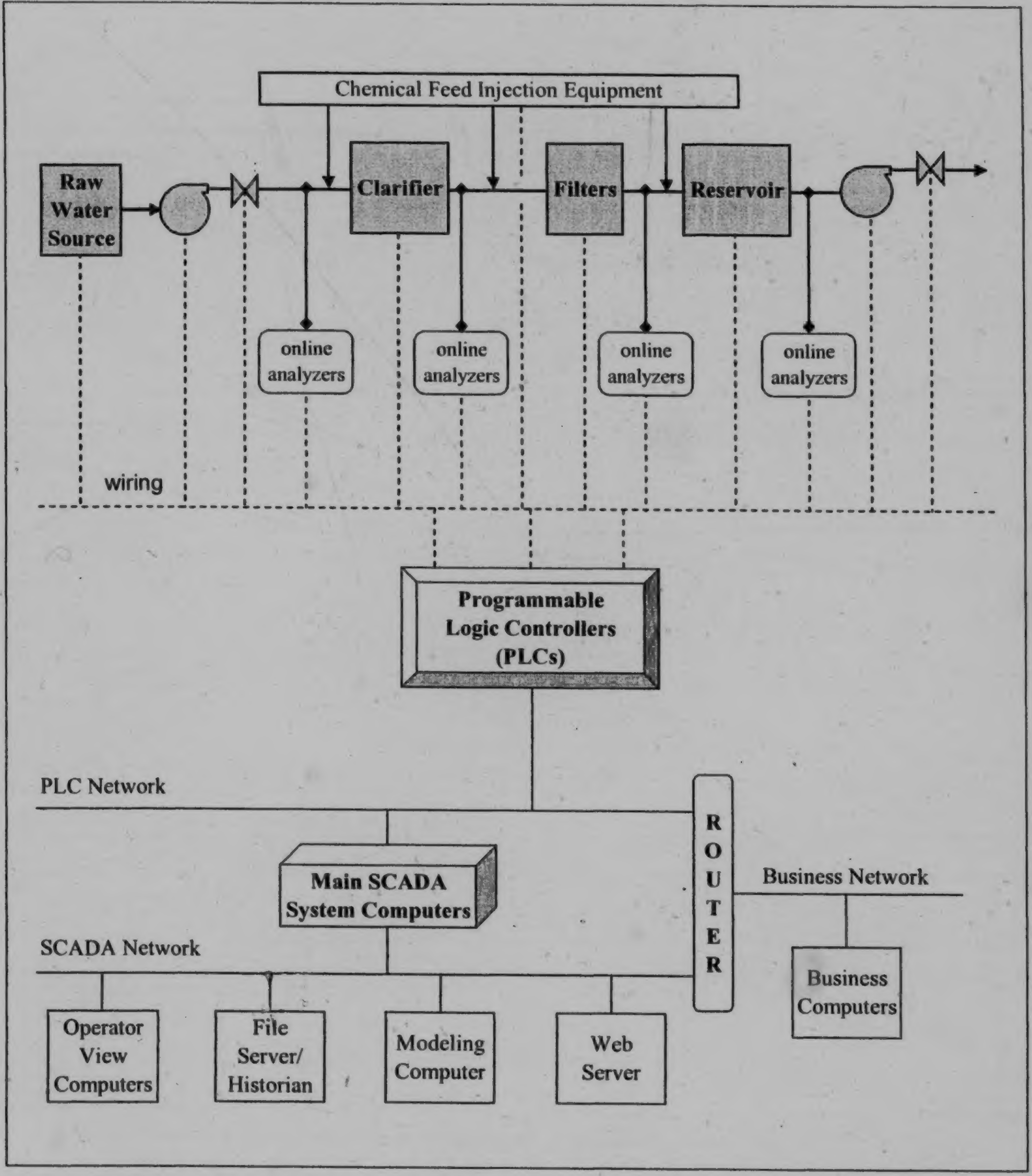

Chemical Feed Injection Equipment
Raw Water Source
Clarifier
Filters
Reservoir
online analyzers
online analyzers
online analyzers
online analyzers
wiring
Programmable Logic Controllers (PLCs)
PLC Network
ROUTER
Main SCADA System Computers
Business Network
SCADA Network
Business Computers
Operator View Computers
File Server/ Historian
Modeling Computer
Web Server

FIGURE 3-8 SCADA system layout for a generic water treatment plant

Plant operators interact with SCADA systems through an HMI (human machine interface) which is typically a computer. Both monitoring and control can be done via the HMI. Several HMI units may be installed throughout a plant to provide quick and easy access to SCADA information. This is accomplished by networking the various hardware components together so that they can communicate. In modern plants, the communication networks can extend to the business side as well (and in fact to the internet if necessary) thereby making it possible to provide real-time SCADA information corporate wide. When a SCADA system is set up in this way, it can reach all types of users such as operators, engineers, researchers, maintenance personnel, managers, inventory control personnel, and others. In essence, a SCADA system is not only a monitoring and control system but in today's plants, due to more involvement by various users, it is also a powerful real-time communication and decision making tool.

The various capabilities and user reach of SCADA systems make them an ideal platform to integrate ANN models effectively for real-time monitoring and control purposes. Although HMI's provide an effective general interface for users to interact with the SCADA system for basic plant operation, specific interfaces need to be developed and implemented for ANN models. These (ANN) interfaces integrate with the control system as well as the HMI.

3.3.1.2 ANN Interfaces

The second key requirement for successful integration of ANN with control systems is ANN interfaces. ANN interfaces are important because they tie all the necessary elements (such as runtime ANN models[*], SCADA system, HMI, control schemes, instrumentation, applications, and so on) together such that reliable, safe, and effective interaction occurs between the operator and control system. This step is crucial to the success of ANN based automatic control of plant processes. As such, the ANN interface can be said to have two basic components: the control interface and the user interface.

---

[*] A runtime ANN model is one that no longer learns from previous examples, is portable as it does not require most of the software that was originally used to develop it, and is capable of making predictions with new input data.

Control Interface

The control interface component interacts in real-time with the SCADA system and when required to, with the user interface. It incorporates the ANN runtime model(s), a control scheme such as the IMC described earlier in this chapter, and conducts input/output operation including accepting control commands from the user interface.

The control interface is the heart of an ANN control system where decisions can be made somewhat autonomously and in real-time. The interface can therefore become quite complex in nature especially if optimization routines (which can require trial-and-error and searching methods to arrive at solutions) are also incorporated. Stability and reliability are therefore some of the important considerations in the design of control interfaces. These features are usually included in advanced control interface designs where additional capabilities are also incorporated. These can include an error handling system (to identify and respond to erroneous data), early detection of problems and alarming, and deactivation of automatic control or even the shutting down of systems if problems escalate beyond established limits.

User Interface

The user interface component is designed to interact with the users of the ANN control system. Through it, users can monitor performance and issue control commands that affect how the ANN control system operates. An effective user interface is one that conceals the more complex nature of the control interface from the user while incorporating user-friendly features for quick and easy interaction. Unlike the control interface which runs continuously, the user interface can be turned on or off without affecting the performance of the ANN control system.

The user interface can be accessed by different types of users depending upon how it is implemented in terms of hardware and software utilized and configured and what access rights the users have been granted. Plant operators would require on-line real-time interaction with the ANN control system and so would likely utilize a user interface viewable on their HMI computers where improved stability, reliability and security are more assured. Other users would not be allowed to issue control commands but may still need real-time monitoring capabilities. User interfaces designed to provide real-time monitoring but not control capability would be more suitable for these users. Figure 3-9 illustrates how the flow of information between the SCADA system, the various interfaces, and users could occur.

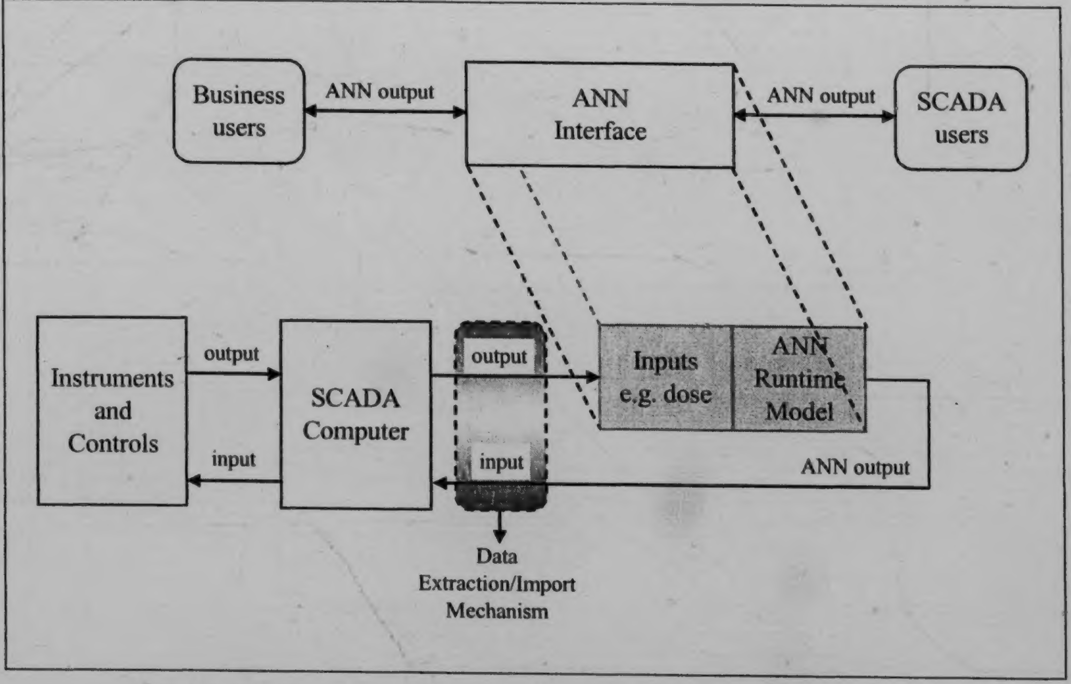

Business users
ANN output
ANN Interface
ANN output
SCADA users
Instruments and Controls
output
input
SCADA Computer
output
input
Inputs e.g. dose
ANN Runtime Model
ANN output
Data Extraction/Import Mechanism

FIGURE 3-9 ANN control system integration information flow

As mentioned, in developing and implementing ANN interfaces, both hardware and software is utilized. Considering the ever increasing power and affordability of personal computers, it is the hardware of choice for most situations. On the software side, many applications and programming languages are available to handle the task especially for standalone use and off-line execution of ANN models. For real-time applications, more thought must be given to the selection of software especially if the interface will be used for automatic control. In this case, reliability and compatibility of the interface software with SCADA software is a must. The use of common infrastructure and more open communication standards can be very beneficial in developing interfaces as they help to reduce the complexity of the interface (while presumably improving reliability), the development time and expertise level required, and the initial and future support costs of the interface. The use of open standards also makes the interface accessible to more users in an organization.

The spreadsheet software called Microsoft Excel® which is commonly available in many organizations can be used to develop ANN interfaces. Many of today's SCADA software use open standards to facilitate communication of information to other applications including with Excel. The Excel software also has a built-in VBA (Visual Basic for Applications) programming capability and so sophisticated algorithms can be developed. With real-time connectivity, user familiarity, advanced programming capability, the versatility of an electronic spreadsheet, and quick development times, Excel is an excellent first choice for developing ANN interfaces. This is especially true during the initial development and testing stages of the ANN control system where changes may occur frequently.

When stability, security, reliability and control beyond the capabilities of Excel are desired, specialized software such as the programming software Visual Basic (VB) or C^{++} can be used to develop custom ANN interfaces. The development time is usually much higher when using programming languages but there is more flexibility in how the interface works and looks. The development time can be reduced somewhat if Excel was used initially to develop the interface because the VBA code in Excel can be largely reused in the VB programming language. Both Excel and VB can be used to develop the control as well as the user interfaces that make up the ANN interface. In addition, both can be used for executing ANN models in real-time or in an off-line standalone mode.

A third system, primarily useful in developing user interfaces, is a web-based system. In this system, the user interface is located on a web page in the company's intranet web server. Since the intranet web site can be accessed with web browsers which are typically built into most computer operating systems, web-based user interfaces can potentially reach all staff in an organization. In addition, since the system is centralized, there is no need to visit the users' desktops to install the interface. Updates to the interface can be deployed quickly and again without visiting the users. This feature alone can greatly reduce the support costs of the ANN interface. Since the web-based interface is primarily useful as a user interface, it needs to interact with a control interface that is developed using either Excel or VB or some other application.

An example of an early development of a VB based and web-based off-line standalone user interface is shown in Figures B-1 and B-2 located in Appendix B. An Excel based real-time ANN interface which includes the control and user interfaces is developed in the following section.

3.3.2 Lime Softening ANN Model Integration with Control System

After ANN models for the Rossdale WTP lime softening clarifier were developed as described in Chapter 2, the models were ported to the Rossdale WTP SCADA system for on-line testing and performance evaluation. Both forward and inverse models of the lime and alum clarifiers were integrated so that real-time predictions of pH, alum dose, total hardness and lime dose requirements could be done.

An ANN interface was developed which included the control interface and the user interface. The control interface ran the four ANN models mentioned above in real-time. For predicting and automatically controlling lime dosages given a total hardness target set-point, a model-based feed-forward control scheme was programmed in the control interface. The scheme also included an integrated real-time inferential (virtual) sensor based pH meter. The need for such a sensor was described earlier in section 3.2.3 and illustrated in Figure 3-7. All the predicted values in the control interface were read back by the SCADA system so that when desired, continuous control of the lime feed dosage could be done automatically.

Although automatic control of the lime dose for the Rossdale WTP Plant 2 clarifier was tested, it was only done for short periods of time to confirm that technically the ANN control system was performing as expected. Instead, for the most part, the ANN control system for the lime softening clarifier ran in a predictive mode twenty-four hours a day making predictions of lime dosages given the actual plants present total hardness value and also what the total hardness should be given the actual plants present lime dose. The real-time predicted values were displayed on the SCADA system HMI and also historized so that the ANN control system's performance could be evaluated at a future date.

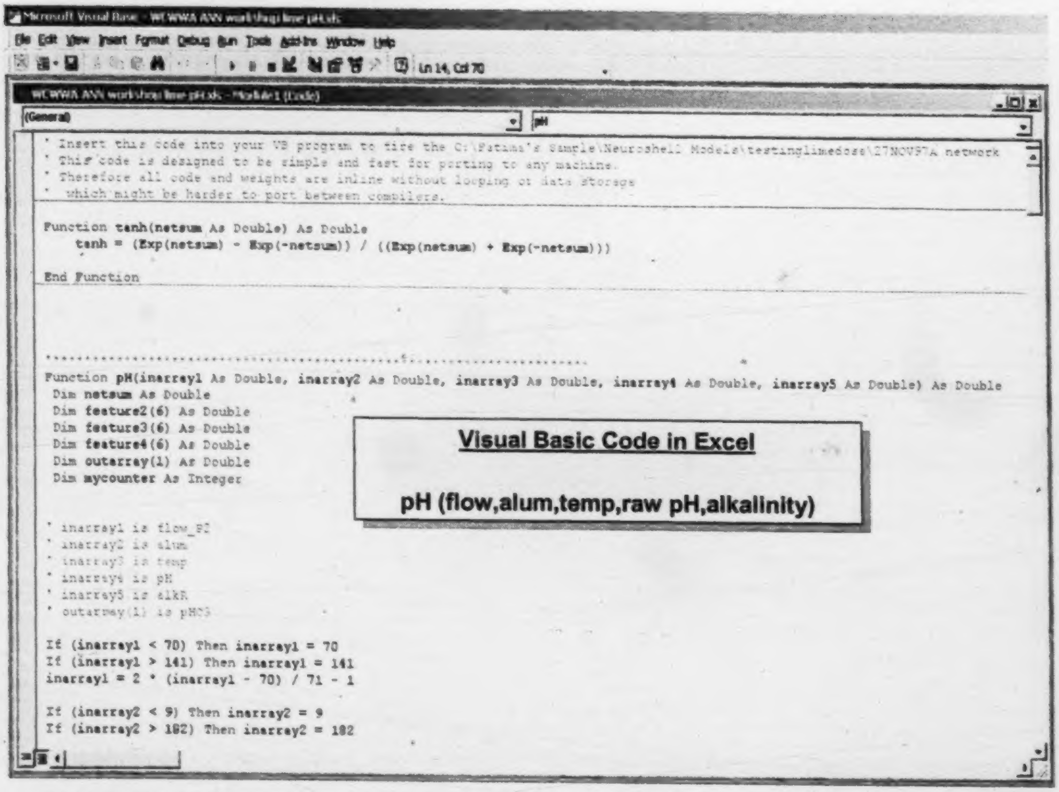
The following discussion deals with the design details of the ANN control system and ANN interfaces that operate in a standalone manual mode or automatically in real-time.

3.3.2.1 ANN Interface for the Lime Softening Clarifier

Integration of ANN models with control systems can begin once the learning process has been completed. A runtime version of the model is required at this stage. Ideally, the runtime model is compatible with familiar Windows applications such as Excel and Visual Basic.

Fortunately, the NeuroShell2 software that was used in developing all the softening ANN models is capable of generating runtime versions of the ANN models and computer code that can be used with minor modification by many different applications including Excel, Visual Basic programming language and Web pages. An example of the computer code generated by the NeuroShell2 software for predicting the alum clarifier pH is shown in Figure 3-10.

The code was added to an Excel VBA program and a function called pH (flow, alum, temp, raw pH, alkalinity) was created for the pH ANN model. This function can be called and manipulated inside an Excel spreadsheet cell much like many other built-in functions such as sin(x) or average(x). Once a function of the ANN runtime model has been created in Excel, an ANN interface can be built. The interface could run in a standalone manual mode or, if integrated with a SCADA system, it could run automatically in real-time.


Microsoft Visual Basic - WCWWA ANN workshop lime pH.xls
File Edit View Insert Format Debug Run Tools Add-Ins Window Help
Ln 14, Col 70
WCWWA ANN workshop lime pH.xls - Module1 (Code)
(General)
pH

```
' Insert this code into your VB program to fire the C:\Fatima's Sample\Neuroshell Models\testinglimedose\27NOV97A network
' This code is designed to be simple and fast for porting to any machine.
' Therefore all code and weights are inline without looping or data storage
'  which might be harder to port between compilers.

Function tanh(netsum As Double) As Double
    tanh = (Exp(netsum) - Exp(-netsum)) / ((Exp(netsum) + Exp(-netsum)))

End Function



'*****************************************************************
Function pH(inarray1 As Double, inarray2 As Double, inarray3 As Double, inarray4 As Double, inarray5 As Double) As Double
 Dim netsum As Double
 Dim feature2(6) As Double
 Dim feature3(6) As Double
 Dim feature4(6) As Double
 Dim outarray(1) As Double
 Dim mycounter As Integer

' inarray1 is flow_PI
' inarray2 is alum
' inarray3 is temp
' inarray4 is pH
' inarray5 is alkR
' outarray(1) is pHC3

If (inarray1 < 70) Then inarray1 = 70
If (inarray1 > 141) Then inarray1 = 141
inarray1 = 2 * (inarray1 - 70) / 71 - 1

If (inarray2 < 9) Then inarray2 = 9
If (inarray2 > 182) Then inarray2 = 182
```

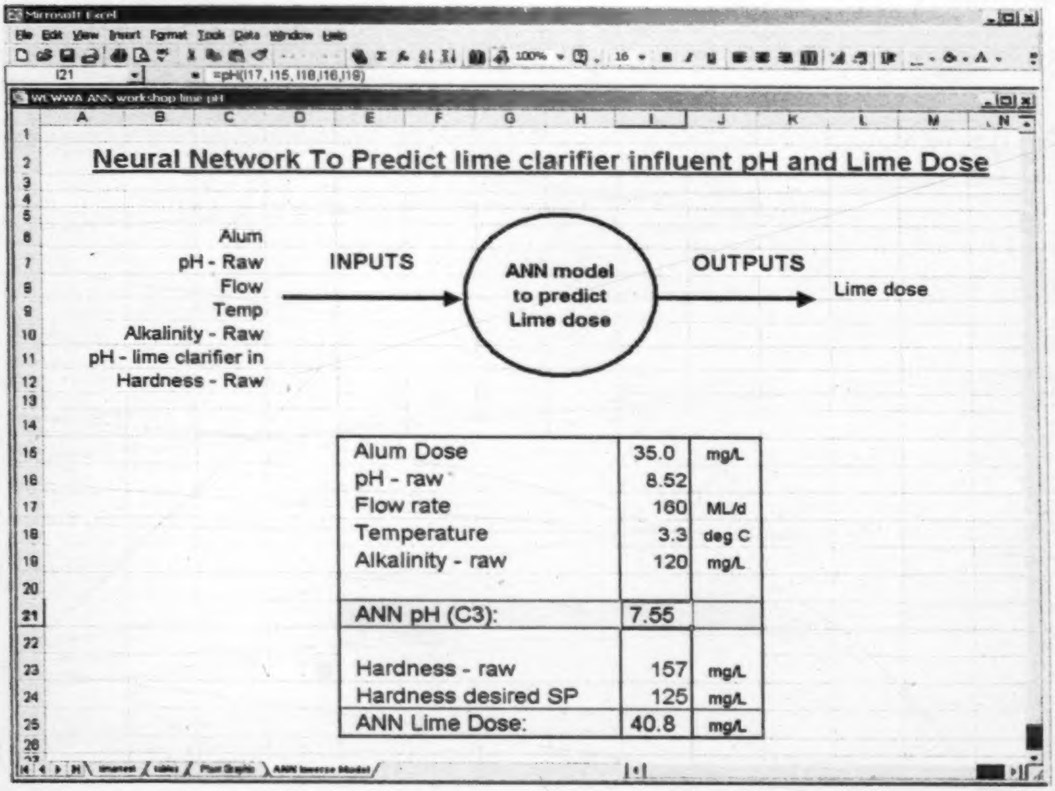
Visual Basic Code in Excel

pH (flow,alum,temp,raw pH,alkalinity)

FIGURE 3-10 Visual Basic code (partial listing) in Excel of a runtime pH ANN model

Standalone Manual Mode ANN interface

Developing an ANN model to run in a standalone manual fashion in Excel is relatively straightforward. Figure 3-11 illustrates how this could be done for predicting pH and lime dose. The required inputs for each model are entered manually in the table. As the values are entered, the ANN model functions in cells I21 for pH and I25 for lime update. Note that for the lime model, the pH ANN model (cell I21) is also an input and it would not be possible to predict the lime dose without it. The standalone manual ANN interface is useful for determining intermittently the value of lime dose. For continuous control however, an ANN interface running in real-time is required.


Microsoft Excel
File Edit View Insert Format Tools Data Window Help
I21
=pH(I17, I15, I18,I16,I19)
WCWWA ANN workshop lime pH
Alum
pH - Raw
Flow
Temp
Alkalinity - Raw
pH - lime clarifier in
Hardness - Raw
INPUTS
ANN model to predict Lime dose
OUTPUTS
Lime dose

Neural Network To Predict lime clarifier influent pH and Lime Dose

Alum Dose	35.0	mg/L
pH - raw	8.52	
Flow rate	160	ML/d
Temperature	3.3	deg C
Alkalinity - raw	120	mg/L
ANN pH (C3):	7.55	
Hardness - raw	157	mg/L
Hardness desired SP	125	mg/L
ANN Lime Dose:	40.8	mg/L

FIGURE 3-11 Standalone manual ANN interface for pH and lime dose

Real-time ANN interface

The standalone manual mode ANN interface can be adapted to run in real-time if it were possible to have the inputs vary automatically and in real-time (as opposed to being manually entered). For example, if the input cells could be linked to the plant instruments then the ANN models would run in real-time. Furthermore, if the ANN model predictions could be read back by the plant control system then automatic control using advanced model-based control would be accomplished. Achieving all this functionality really depends upon whether appropriate instrumentation exists and whether a compatible SCADA system is available to move information back and forth between it and the Excel interface.

At the Rossdale WTP, there exists appropriate instrumentation and compatible SCADA system software (FIX32 by Intellution®) such that development of a real-time interface can be attempted. The design of such an interface begins with an illustration of how information flows between the various systems as shown in Figure 3-12.

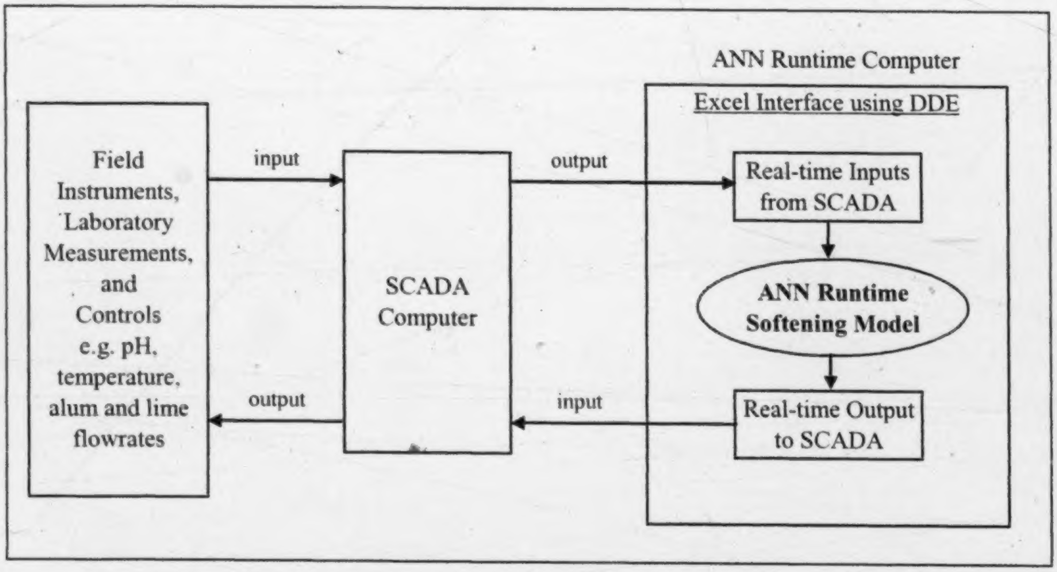
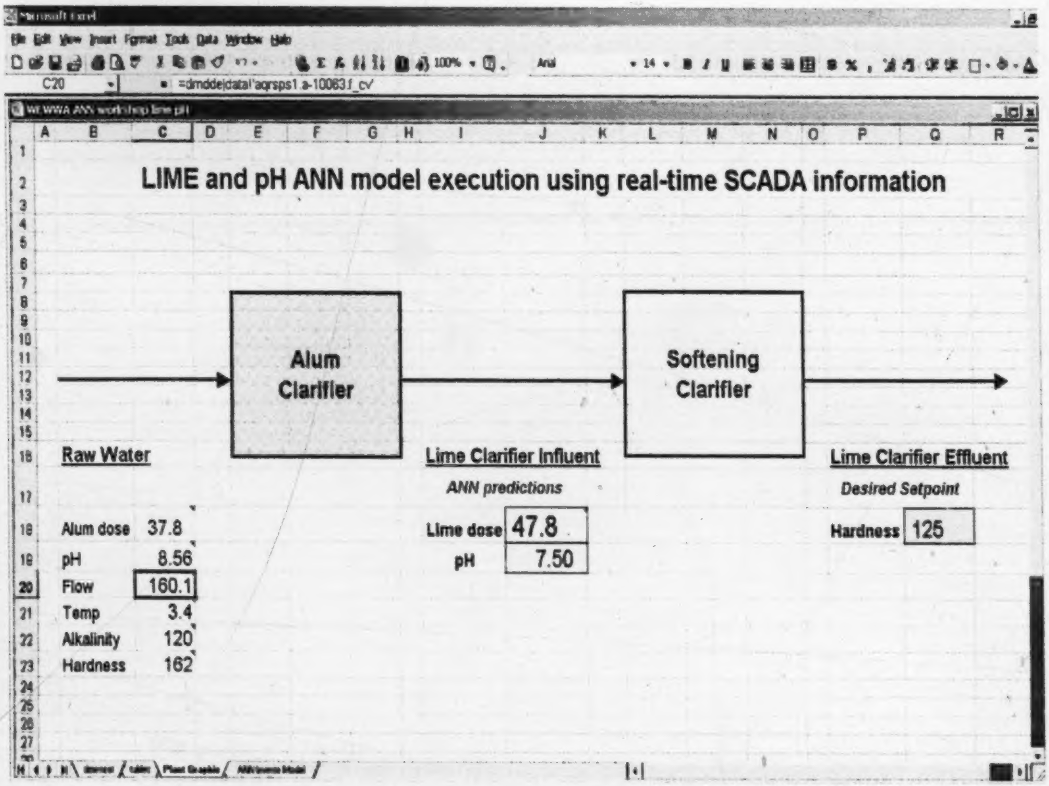

ANN Runtime Computer
Excel Interface using DDE
Field Instruments, Laboratory Measurements, and Controls e.g. pH, temperature, alum and lime flowrates
input
output
SCADA Computer
output
input
Real-time Inputs from SCADA
ANN Runtime Softening Model
Real-time Output to SCADA

FIGURE 3-12 Real-time information flow path for the softening ANN control

The Intellution® SCADA software provides a communication protocol based on a Windows standard known as Dynamic Data Exchange (DDE). This allows the exchange of information to occur between the Excel based ANN interface and the SCADA in a two-way real-time manner with update rates of less than one second. Consequently when data from the field instruments is received by the SCADA, it can be passed over to the Excel interface almost instantaneously. The ANN runtime models therefore also update almost instantaneously generating predicted values for lime dose, total hardness, pH, and alum dose. These values can be read by the SCADA software as analog inputs (see Figure B-3 in Appendix B) using the same DDE protocol for display on the HMI or for automatic control of the lime feed dose. The real-time interface of the softening clarifier is shown Figure 3-13. The data in all the cells are either inputs or outputs and each one updates in real-time.


Microsoft Excel
File Edit View Insert Format Tools Data Window Help
100%
Arial
C20
WEWWA ANN workshop lime pH
A B C D E F G H I J K L M N O P Q R
Alum Clarifier
Softening Clarifier

C20 =dmdde|data!'aqrsps1.a-10063.f_cv'

LIME and pH ANN model execution using real-time SCADA information

Raw Water
Alum dose 37.8
pH 8.56
Flow 160.1
Temp 3.4
Alkalinity 120
Hardness 162

Lime Clarifier Influent
ANN predictions
Lime dose 47.8
pH 7.50

Lime Clarifier Effluent
Desired Setpoint
Hardness 125

FIGURE 3-13 Real-time ANN interface for pH and lime dose

The real-time ANN interface developed thus far incorporates both the Control and the User interfaces as defined in section 3.3.1.2. An enhancement to the user interface would be to have it displayed and controllable from any HMI computer by an operator. Since the data is already available in the SCADA, a screen can be developed displaying the appropriate information and controls. This is shown in Figure B-4 in Appendix B. Note the Auto/Manual control mode feature in the screen display. By selecting Auto or Manual mode, an operator can decide whether lime dose control should be done automatically with the model-based control system using ANN or by the operator manually entering values.

The data generated by the ANN Control system can also be historized in the plant SCADA system for future performance evaluation. The results for the on-line ANN control system for the softening process have been previously discussed in Chapter 2. A trend of the lime dose and total hardness actual and predicted values was extracted from the SCADA historian and is shown in Figure B-5 in Appendix B.

3.4 Looking to the Future

It has been said that one of the major challenges facing process engineers is the reduction of variable costs while still maintaining product quality, and that advanced process control is the most effective technology available to realize this objective (Willis and Tham, 1994). In the future, artificial neural networks are likely to play a larger role in process industries by fulfilling one of the main requirements for implementing model-based advanced controls – accurate models of processes.

For water treatment plants, the ability to model processes more accurately and affordably will improve the possibility of implementing plant-wide control and management systems. These are systems that link multiple models (process, energy use, production capability, demand forecasting, quality, costs) into a constraint based decision making system. Essentially, plant-wide control and management systems relate directly to overall plant management objectives by linking business objectives with local unit operations.

With increasing use of models, advanced control systems, plant-wide control and management systems, and efficient interfaces, sharing of information by the various systems and users across the whole corporation in a reliable, secure, efficient, and timely manner becomes a necessity. Therefore the use of more open systems (as opposed to proprietary solutions) especially in the data communication field, and standards for hardware, software and programming techniques will become more important.

As drinking water quality regulations become more and more stringent, not only average target values but also instantaneous target values for parameters such as turbidity and particle counts are decreasing. This increases the need for tighter controls to prevent water quality violations. Due to large time delays inherent in water treatment processes, there is greater need to have accurate and continuous feed-forward type control at various stages of the process so that adjustments can be made on a timely basis. On-going training of operators to manage the more sophisticated plant-wide controls is also important. Fortunately, once models have been developed for the plant, they can be used not only for automatic control but also for simulating the plant which can be a very useful tool for training operators to deal with especially difficult water treatment conditions (e.g. spring runoff).

The role of SCADA Historians which collect and store plant information is increasing from basic report preparation and trending to becoming an integral part in the development of models and in providing data in near real-time for enhancing control. The use of historical data for developing models in an off-line manner has been shown in Chapter 2. However, models could also be developed on-line automatically using data from the historian. On-line updating of models could improve the response to out-of-domain data. One caveat to on-line ANN model development is the need to identify and remove erroneous data as this may decrease the accuracy of the models and degrade control. A possible method to improve responsiveness while still maintaining accuracy is by developing long-term and short-term models. Long term models would be developed off-line and geared towards accuracy, reliability and robustness while short-term models would be developed on-line to be more responsive to changes in the process. Final outputs would be determined by first comparing the outputs from both models and then applying appropriate techniques for making a final decision (the technique could be as simple as averaging the outputs of each model). Should large differences in the predictions between the models occur, appropriate alarming could be generated. If the difference continues for a longer period, it could indicate that the long-term model requires re-training.

3.5 Conclusions and Recommendations

This chapter has described the inadequacies of traditional PID controllers for controlling some water treatment processes, and the growing need for using model-based advanced control techniques for improving process control, automation, and costs. A major requirement of model-based control techniques is accurate models of processes and this is where ANN can be used.

A vital step towards the implementation of advanced controls is the successful integration of ANN based models with plant real-time process control systems. This can be done by first choosing a control scheme such as the ideal model-based control scheme or the more sophisticated IMC (internal model control) scheme. Additional requirements for real-time integration include a SCADA system, communication networks, on-line instrumentation, and an ANN interface. It should be pointed out that advances and expertise developed with these technologies has also led to applications for remote operation of plants. This is described in detail in the following two chapters of this thesis.

It was shown that ANN models for water treatment can be integrated with real-time control systems to make continuous predictions and to control processes. An actual ANN control system for the Rossdale WTP softening process was developed and tested. ANN models developed in Chapter 2 were integrated into the plant SCADA system using a feed-forward model-based control scheme with a real-time pH inferential sensor. An Excel based ANN interface was developed to execute the scheme and to interface with operators. It is also possible to develop interfaces using a VB programming language or web pages. Web-based interfaces are particularly useful as they make ANN interfaces more easily available to users corporate wide. However, proper security measures must be applied to web-based systems particularly if the interface allows control capability.

The main goal of this phase of work was to develop and test a real-time ANN control system and so, except for brief periods of time for testing the automatic control of lime feed dosages, the system was run in a predictive mode. Based on feedback from users and the performance of the model, this phase of work was successful and the experience gained shows that continuous automatic control is viable and should be the logical next step for testing. It should be mentioned that this is no longer possible at Edmonton's WTP's due to the stoppage of softening in early year 2000.

The techniques developed in Chapter 2 in developing softening models should be useful for developing models for other softening plants. The integration techniques developed in this chapter are not unique for the softening process and so they could be applied to many other process automation problems. Since an on-line analyzer for measuring total hardness was not available at the Rossdale WTP, feed-back control using the more advanced IMC scheme was not attempted. It is recommended that if other trials are done, such an analyzer should be acquired as it may provide finer control. Finally, maintaining reliability and accuracy of the ANN control system with time is an important area for further research. Specifically, out-of-bound input detection, error detection and data handling techniques, model drift detection methods, and long-term/short-term ANN modeling systems are areas that need to be investigated further.

3.6 References

1. Baxter, C.W., Tupas, R.T., Zhang, Q., Shariff, R., Stanley, S.J., Coffey, B.M., Graff, K.G. (2001). Artificial Intelligence Systems for Water Treatment Plant Optimization. American Water Works Association Research Foundation Report No. 90861. Denver, CO. 141 p.

2. Bhat, N. and McAvoy, T.J. 1990. Use of Neural Nets for Dynamic Modeling and Control of Chemical Process Systems. Computers and Chemical Engineering. 14, 4/5, 573-583.

3. Deshpande, P. B. and Yerrapragada, S. S. 1997. Predict difficult-to-measure properties with neural analyzers. Control Engineering Online. <http://www.manufacturing.net/magazine/ce/archives/1997/ct10701.97/07e503.htm >

4. Gotoh, K., Jacobs, J.K., Hosoda, S., Gerstberger, R.L. 1993. Instrumentation and Computer Integration of Water Utility Operations. Denver, CO. AWWARF and JWWA. 476 p.

5. Intellution® Inc., (1997). FIX32 SCADA Software version 6.15, Foxborough, MA.

6. Morari, M. and Zafiriou, E. 1989. Robust Process Control. Prentice-Hall. 512 p.

7. Psichogios, D. C. and Ungar, L. H. 1991. Direct and Indirect Model Based Control Using Artificial Neural Networks. Ind. Eng. Chem. Res. 30, 2564-2573.

8. Schlenger, D. L., Riddle, W. F., Luck, B. K., Winter, M. H. (1996). Automation Management Strategies for Water Treatment Facilities. American Water Works Association Research Foundation Report No. 90676. Denver, CO. 195 p.

9. Shariff, R., Cudrak, A., Stanley, S. 2001. Remote Monitoring and Operation of Isolated Facilities in Cold Regions. Proceedings, AWWA Annual Conference, Washington D.C., June 2001.

10. Shinskey, F.G. (1996). Process Control Systems: application, design, and tuning, 4th edition, McGraw-Hill Co. Inc., New York. 439 p.

11. Stanley, S.J., Baxter, C.W., Zhang, Q. and Shariff, R. (2000). Process Modeling and Control of Enhanced Coagulation. American Water Works Association Research Foundation Report No. 90784. Denver, Colo. 146 p.

12. Stanley, S.J., Sacken, Von E., Baxter, C.W., Shariff, R., Zhang, Q., Coffey, B. 2001. Improving Water Utility Management Through the Use of Artificial Neural Networks with Utility Operating Systems. AWWA Annual Conference Workshop S2, Washington D.C., June 2001.

13. Tham, M. T. 2000. Inferential Measurement and Control, <http://lorien.ncl.ac.uk/ming/infer/infer.htm >

14. VanDoren, V. J. 1998. Basics of Proportional-Integral-Derivative Control. Control Engineering Online. <http://www.manufacturing.net/magazine/ce/archives/1998/ct10301.98/03a305.htm>

15. Ward Systems Group Inc, (1996). NeuroShell 2 version 3 Neural Network Software, Frederick, MD.

16. Willis, M. J. and Tham, M. T. (1994). Advanced Process Control, <http://lorien.ncl.ac.uk/ming/advcontrl/apc.htm >

17. Zhang, Q. (1996). Artificial Neural Networks and their Application to Water Treatment, M.Sc. Thesis, Department of Civil and Environmental Engineering, University of Alberta, Edmonton. 145 p.

4.0 REMOTE MONITORING AND OPERATION OF ISOLATED SMALL WATER FACILITIES IN COLD REGIONS

4.1 Introduction

Many small communities in Canada are isolated which poses unique problems in operation and maintenance of water treatment and supply systems. As a result of this isolation, availability of manpower and technical expertise to operate and maintain water treatment systems can be a challenge. Regular access to facilities may also be difficult during winter conditions and because facilities may be long distances apart.

In Chapters 2 and 3, it was shown that several technologies such as ANN modeling, on-line analyzer systems, SCADA systems, data historians, and communication systems must be integrated and work in harmony when implementing advanced automation techniques. Consequently, these technologies have been advancing and the expertise developed in those areas has also led to applications for remote facilities including the development of QA programs for testing and proving on-line analyzers, remote communication systems to monitor the performance of the remote plants, and utilization of SCADA systems (local and wide area) to provide monitoring, control, and data historization. These technologies are expected to have a significant impact in improving drinking water quality and consistency in remotely located plants particularly those that are small and isolated (Shariff et al, 2001).

This chapter describes the benefits and challenges of remote monitoring and operation of isolated small water facilities. A pilot study of commercially available on-line chlorine residual analyzers is also covered in this chapter.

4.2 Background

Approximately 85% of all community water systems (CWS) in the United States serve less than 3,300 people (USEPA, 2001). Most small utilities face significant resource challenges and their systems typically lack on-line monitoring and control equipment, alarming systems, and automatic shutdown systems to protect water quality. Qualified operators are also difficult to acquire and keep, particularly in isolated regions. As a result, small systems have performance problems and much higher incidences of water quality violations. A study of drinking water quality in Northern Canada (Armstrong et al, 1996) found that small systems in the study region had higher treated water turbidity than larger systems and also had the highest percent of coliform positive samples. The USEPA (2001) reports that 86% of systems in violation of the MCL (maximum contaminant level) are also the ones that serve less than 3,300 people.

The most common source for small systems is groundwater and many treatment facilities rely solely on chlorination for the treatment of the potable water. Figure 4-1 illustrates a simple groundwater chlorination treatment system.

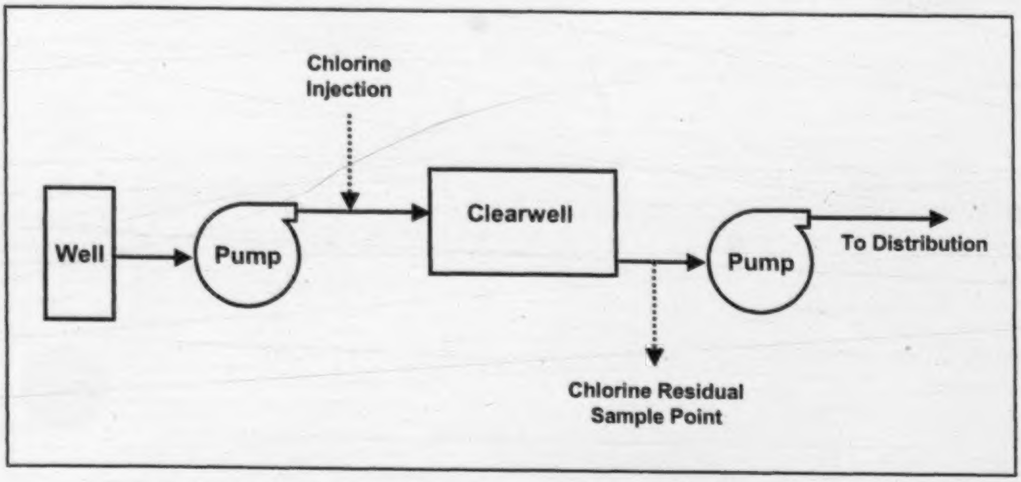


FIGURE 4-1 Groundwater source plant using free chlorine

For many small utilities, the current monitoring practice consists of employees conducting manual chlorine residual tests once a day during the week with an absence of any type of monitoring or testing on the weekends. In the event of a chlorinator breakdown, it may be up to 72 hours before employees are even aware that a problem exists and are able to respond. Indeed, there is a possibility that non-ideal quality water is being pumped unknowingly at any time due to undetected intermittent variations in water flow and chlorine feed rates. The effects of a bacterial outbreak in a water distribution system due to a lack of chlorination can have devastating effects (for example, Walkerton, Ontario in year 2000).

In northern locations, there are additional risks due to cold air temperatures and accessibility issues. Reliability of equipment can be an issue due to power failures being more common in cold climates. Controls equipment can be adversely affected by low temperature or high humidity and needs to be protected in special cabinets (Smith et al, 1986). A lack of available manpower, isolation, and obstructed facility access during cold conditions mean that delays in visiting the plants are possible on any given day which further increases the risk of violations.

To summarize, the challenges faced by small systems in cold regions include:

- Long distances between facilities.
- Obstructed access during bad weather conditions.
- Low reliability of equipment in cold air environment.
- Low performance from sensor equipment in cold water temperatures.
- High turnover of staff.
- Treatment challenges due to cold water temperatures.
- High rates of water quality violations.
- Low technical, financial, and managerial capacity.

To gain improvements in water quality and consistency, the application of technology can help small water systems just as it does larger water plants. Early detection and prompt response to problems would help reduce the risk of non-ideal water (water that is not meeting quality guidelines) from entering the distribution system. For example, if non-ideal water could be detected in time, the plant could be shut-down automatically or the water could be diverted to waste. Assuming that there was enough available storage capacity (a prudent strategy), water supply could be maintained for a period of time while the problem is getting addressed.

Additional monitoring and control equipment along with a commitment to maintain small systems can be very beneficial but in some cases can be very expensive. In general, the initial cost of equipment is not as important as its reliability and this is especially true in cold regions due to challenging conditions (Smith et al, 1986). The overall challenge then is to come up with systems that are reliable, maintainable, produce acceptable quality water, and are affordable. Three components are presented next which can help meet some of the challenges faced by small systems, and in particular, small systems in cold, isolated regions. They are:

- Continuous water quality monitoring and control using on-line analyzers.
- Remote communication systems.
- SCADA (supervisory control and data acquisition) systems for alarming, control, data logging, reporting, troubleshooting, and to assist with process improvements.

4.2.1 On-line Analyzer Systems

Regular and frequent water quality monitoring is an important aspect of water plant operations that helps prevent non-ideal water from entering the water supply system. Consequently, the use of on-line analyzers is growing, especially in medium to large sized water plants. In fact, regulators are beginning to require continuous monitoring of water quality parameters such as residual chlorine, turbidity, pH and others (Shariff and Thomas, 2001). The number of vendors supplying on-line analyzer equipment also seems to be increasing leading to increased competition which benefits end users in terms of cost and performance of the analyzers

The alarms generated by on-line analyzers can be used to trigger the shutdown of a system or the plant. When the continuous data produced by the on-line analyzers is integrated with control systems such as chlorine residual control, the consistency of water quality is improved and problems are prevented.

When selecting a specific water quality monitoring and control device, certain features need to be considered (Pollack et al, 1999):

- **Sensitivity.** Is the sensor able to measure the parameter at the lower limit of the regulatory requirement?
- **Reliability.** Is the sensor able to supply stable and reliable performance over an extended period of time? Are there any previous users or literature that support this?
- **Maintenance Requirements**. Does the sensor require extensive maintenance? Are there any consumables, such as probe solutions, that demand frequent manual replenishment?
- **On-line design.** Can it be incorporated such that on-line calibration and remote validation of performance is possible?
- **Amenability/Compatibility.** Are the sensor power demands and signal inputs/outputs compatible with other components?
- **Cost.** Is the cost of the sensor such that the overall expense of the remote monitoring system makes it a viable option compared with manual site monitoring?

For an on-line analyzer system to perform successfully, especially one that is depended on for extended periods of time without re-calibration, a commitment of resources to a quality assurance program is necessary. Many larger water plants have an in-house contingent of maintenance and quality assurance personnel along with the equipment necessary to conduct quality assurance on basic and sophisticated analyzers. Analyzers located in remote locations, however, are likely to not have this luxury due to cost and practical limitations. Analyzers that are better suited for these locations are the ones that require less maintenance and are simpler to calibrate and fix while providing readings that are precise and reasonably accurate at all times.

For small water plants, chlorination is the preferred method of disinfection and measurement of residual free chlorine is therefore required. There are several manufacturers of continuous on-line analyzers measuring free chlorine residual using different measurement techniques including amperometric, iodometric, polargraphic, and DPD colorimetric. Some use reagents while others do not and the frequency of servicing and costs vary substantially.

The cost of chlorine analyzers including installation was recently (2001) determined to be between $6,500 and $13,000 (Shariff et al, 2001). Depending on the instrument picked, the yearly operating costs (servicing, reagents, travel) can vary substantially as well – between $600 to $4,000. The quality of the water in the various systems can affect the performance of on-line analyzers. High levels of calcium carbonate can cause deposits on electrodes which will increase the frequency of routine cleaning. The presence of bromide in water causes interference due to bromine responding as chlorine and can decrease the accuracy of colorimetric on-line chlorine analyzers due. Fluctuation in pH can also affect the accuracy of some chlorine analyzers. Finding the right analyzer for a particular application requires study of the water quality, and operating costs. A pilot test of different analyzers for the application in question prior to purchasing is strongly recommended.

Turbidity measurement in small treatment facilities is also common. There are various technologies for continuous measurement of turbidity including light scattering at 90 degrees, infrared LED's and detectors, and the ratiometric four-beam method. For lower values of turbidity measurement, there are sensors available that can measure turbidity accurately for longer periods between servicing and calibration than, for example, residual chlorine analyzers.

4.2.2 Remote Communication Systems

Remote communication systems allow information to flow between the remote sites and a centralized location thus allowing monitoring and control without having to travel to the facility. Many alternatives for communication systems exist today and newer, cheaper, and faster methods are being developed all the time. The internet is beginning to be used more and more to transmit and receive information from site to site and/or to distribute live information anywhere in the world. The ubiquitous dial-up telephone system is still being used extensively due to its extensive range and simplicity. The various technologies being used for data transmission have been summarized by Pollack et al. (1999) and include:

Telephone. Readily available, easily deployed, extensive range, and generally low cost per call but can increase dramatically if dedicated or long distance lines are used with continuous data flow.

Cellular. Uses the cellular network. Range is growing with time but may not be feasible for very remote sites. Cost per call higher than regular telephone.

Radio waves. Fast response time and continuous monitoring, does not require any wires. Startup and maintenance costs higher, low range, line of sight required.

Satellite. Extensive range. Start-up and per call costs high but expected to decline in the next few years.

The final choice as to which communication system is used will depend on what is available at the facility and costs. It should be mentioned that as more and more reliance gets placed on remote communication systems for operating plants, backup systems and procedures must be in place to handle failures. These may include redundant communication links, local automatic plant shut-down systems in case water quality is compromised during a communication outage, and emergency response plans.

4.2.3 Supervisory Control and Data Acquisition (SCADA) Systems

SCADA refers to two separate functions – supervisory control is the remote control of devices such as pumps and valves while data acquisition is the acquisition of data as such flow, pressure, speed, or on-line analyzer readings from remote sensors (Gotoh et al, 1992). The reader is referred to Chapter 3 where a detail description of SCADA systems has been provided.

With the advent of personal computers and off the shelf software, SCADA systems have become more affordable than in the past. Still, it is a difficult cost to bear for many small community water plants and consequently, many of them either do not have one or have a very limited system. There are ongoing requirements for hardware, software and support by technical experts that are necessary to keep a SCADA system functioning properly and this can also become a burden that is difficult to manage by small communities, primarily due to budgetary constraints. Yet, the advantages of having a SCADA system are being recognized more and more by smaller utilities to improve monitoring and safety of their water.

Clearly, a more affordable system would go a long way towards helping smaller communities to ensure their water is safe at all times. Newer technologies and the leveraging of existing ones such as the internet are thought to help with this situation. The concept of a 24-hour manned central control center through which monitoring and control of multiple remote small water plants is done will make the SCADA system function available to small systems at a lower cost due to economies of scale (Shariff et al, 2002). Reliable on-line analyzers can permit extended unattended operation which would help reduce manpower and transportation costs for daily on-site visits. These concepts are explored further in the pilot study described below.

4.3 Pilot Study

In late 2000, a proposal was put forward by EPCOR Water Services (Edmonton, Alberta, Canada) to design a system that could monitor several small water treatment plants in remotely located communities. The plants in question did not have any on-line analyzers and were only being monitored once a day during weekdays (no monitoring on the weekends). The proposal suggested installation of on-line analyzers and remote communication systems at the various plants with centralized 24-hour a day monitoring from the main control room located at one of EPCOR's water plants in Edmonton. A feasibility study was completed which indicated that the concept could be financially acceptable and beneficial for small communities. A pilot study was initiated in early January 2001 to assess the reliability and costs of operation of on-line analyzers, remote communication, and SCADA operations.

4.3.1 Objectives

The types of analyzers suited for small systems in cold regions are the ones that are less prone to failure in low air and water temperature environments, require infrequent upkeep and servicing, are not very complex so that they can be serviced by local staff, consistently provide accurate data, and have low operating costs. Remote communication systems also need to be less complex so that they can be easily fixed should a problem occur. Remote communication systems that require less infrastructure at the remote sites would be ideal.

The specific objectives of the pilot free chlorine analyzer test were:

- To test a variety of commercially available on-line chlorine residual analyzers for use in unattended remote water plants.
    i. identify analyzers that can reliably measure chlorine residual for at least 10 days at a time without requiring servicing.
    ii. determine the accuracy of the analyzer.

    iii. determine the cost of operation and maintenance of the analyzer.
    iv. determine the skill levels necessary to maintain the analyzer.
    v. make recommendation for selecting analyzers with the above considerations in mind.

- To document the capital and operating costs of the various means of communicating with the remote water plants. To test the option of remote communication using the internet.
- To look at options for SCADA for managing the remote water plants.

4.3.2 Pilot Setup

A pilot test setup was installed at one of EPCOR's water treatment plants and consisted of five different chlorine analyzers. A review of the different units was conducted and suppliers were contacted to see if they would loan a unit for testing. Each supplier was asked to assist in the initial setting up, startup and calibration (where necessary) of their equipment. This was meant to ensure all analyzers were equally ready to go from the start.

4.3.2.1 On-line Chlorine Residual Analyzers

Although there are several methods to measure chlorine residual on-line, two methods are used most commonly in water plants: amperometric and colorimetric DPD (N,N-diethyl-*p*-phenylenediamine sulphate) (Shariff and Thomas, 2001). Amperometric measures a potential generated at three electrodes while the colorimetric DPD measures a colour change when an indicator is added to the liquid sample. Both methods require periodic refilling with buffer or electrolyte solution. The amperometric has the potential for faster response since it is measuring continuously, but this depends on configuration and flow rate through the analyzer (Shariff and Thomas, 2001).

Amperometric analyzers require a pH meter to properly estimate the chlorine residual. The advantage of this is that pH is being measured continuously which can be useful.

The disadvantage is that it could cause erroneous chlorine residual readings if the pH meter is not working properly. The colorimetric DPD method uses a buffer solution to adjust the pH before taking the measurement, and therefore does not require a separate pH meter. A disadvantage of the colorimetric DPD method is that other oxidants apart from free chlorine (such as bromine) will be registered in the analysis if they are present in the water.

Four of the units used in the pilot test were amperometric and one was colorimetric DPD. Table 4-1 shows the specifications of each analyzer while Table 4-2 provides additional built-in or optional features of each analyzer.

TABLE 4-1 Specification of each analyzer as quoted by the manufacturer

Analyzer	Type	Range (mg/L)	Quoted Accuracy (mg/L)	Response Time (s)
ProMinent	Amperometric	0 - 2	0.01	1
W & T Depolox 3+	Amperometric	0 - 5	0.01	20
Swan FAM Trides	Amperometric	0 - 3	0.06	60
HACH CL17	Colorimetric	0 - 5	5%	150
Endress & Hauser (E & H)	Amperometric	0 - 5	0.01	1

TABLE 4-2 Additional built-in or optional features of each analyzer

Analyzer	Measurement Type	Other features
ProMinent	Amperometric	pH electrode to compensate for small pH changes in the sample. Flow meter to measure sample flow rate.
W & T Depolox 3+	Amperometric	Test unit did not have a pH compensation system although it is possible to equip the unit with one.
Swan FAM Trides	Amperometric	pH electrode to compensate for pH changes. Flow control system for sample flow regulation. Two temperature compensation probes.
HACH CL17	DPD Colorimetric	Uses a buffer to eliminate the need for pH compensation.
Endress & Hauser	Amperometric	pH electrode to compensate for pH changes.

4.3.2.2 Pilot Design and Experimental

The pilot trial took place in the analyzer room at the Rossdale WTP located beside the filter gallery. A board was set up and all five analyzers were mounted side by side. A common header was used to feed water to analyzers. Several trials were done to test different chlorine concentrations. Free chlorine is used in most communities. The treated water in Edmonton is chloraminated, so water for the test had to be obtained prior to the ammonia injection point.

The concentration of free chlorine within the Edmonton plant is typically > 2 mg/L which is likely higher than many plants that use free chlorine as their sole disinfectant. To mitigate this, an independent loop was created allowing free chlorine levels to fluctuate to the analyzers. A tank was set up that could be filled with water from the effluent line of one of the filters (filter #5) prior to ammonia addition. The water in the tank could then be recirculated to reduce water loss and track the steady decrease in chlorine residual over time. To reduce water loss, water from the four amperometric meters was returned to the tank. Photographs of the pilot setup are shown in Figures C-1 and C-2 in Appendix C while Figure 4-2 illustrates the general mechanical and communication connections.

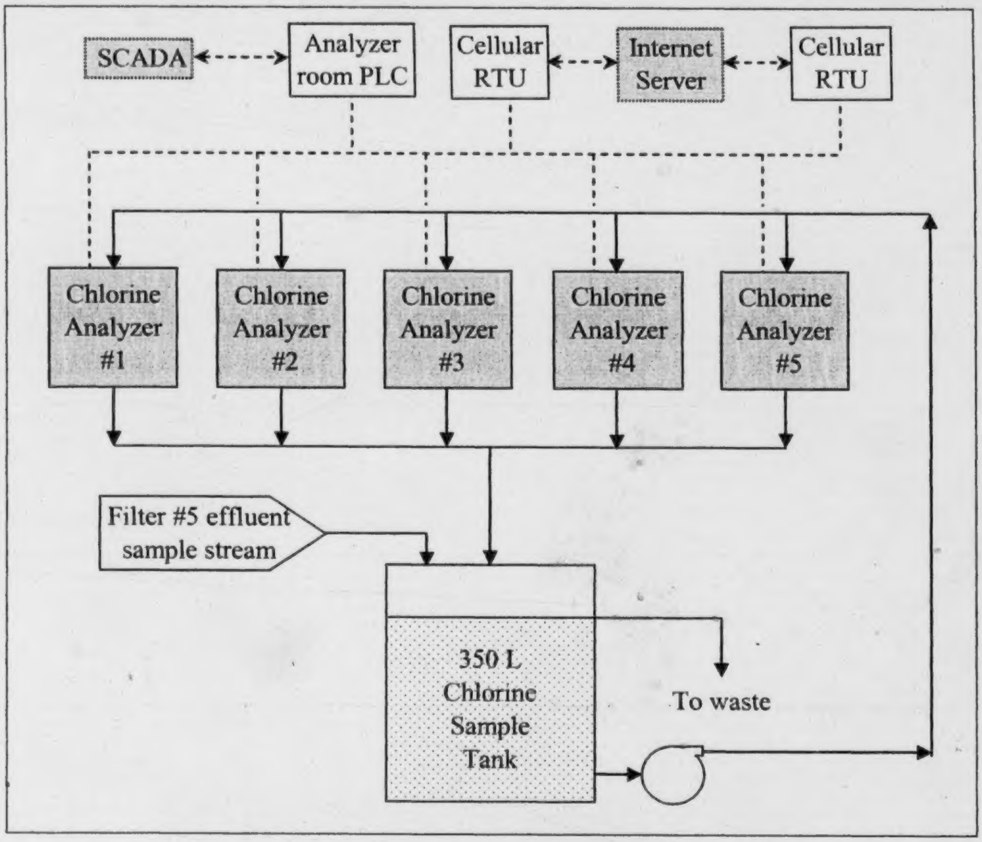

SCADA
Analyzer room PLC
Cellular RTU
Internet Server
Cellular RTU
Chlorine Analyzer #1
Chlorine Analyzer #2
Chlorine Analyzer #3
Chlorine Analyzer #4
Chlorine Analyzer #5
Filter #5 effluent sample stream
350 L Chlorine Sample Tank
To waste

FIGURE 4-2 Schematic of chlorine analyzer pilot test

The analyzers were connected directly to one of the plant's PLC's (Programmable Logic Controllers) and as well to two RTU (Remote Terminal Unit) test units manufactured by ROM COMM Systems, which also contained an integrated cellular communication system to transmit data on an hourly basis to a centrally located server on the internet. Any alarms generated by the RTU were transmitted immediately to the server and could potentially be also used to shut off equipment (auto-shutdown) on an actual water plant. The information from the internet and from the local PLC's was integrated with the main water plant's SCADA system so that the data could be compared side by side.

The RTU with the built-in cellular communication system is very easy to install and commission, and costs less than $1,000 with monthly cellular link charges around $50. The real-time data from each analyzer can be displayed on a web browser on any computer with an internet connection with appropriate user rights. In addition, the analyzer readings can be incorporated into a centrally located SCADA system. As more and more remote sites are integrated, the advantages of a SCADA system can be brought to small remote plants at a much lower cost. Figure 4-3 depicts the layout of the internet based communication link for the pilot study.

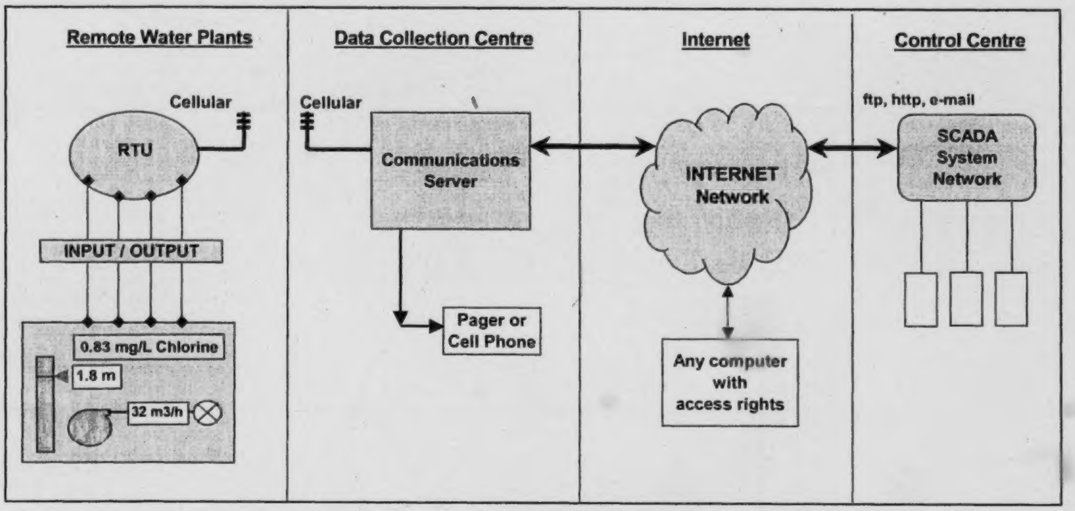

Remote Water Plants
Data Collection Centre
Internet
Control Centre
Cellular
RTU
INPUT / OUTPUT
0.83 mg/L Chlorine
1.8 m
32 m3/h
Cellular
Communications Server
Pager or Cell Phone
INTERNET Network
Any computer with access rights
ftp, http, e-mail
SCADA System Network

FIGURE 4-3 Pilot Study Internet Communication Layout

For comparison purposes between the on-line analyzers and bench meters, grab samples were taken three times a day and measured on a bench chlorine analyzer. A Wallace and Tiernan amperometric bench titrator (see Figure C-3 in the Appendix) similar to that used by the Rossdale Operators and Laboratory personnel to measure Edmonton's drinking water free chlorine residual was used for the bench analysis.

4.3.3 Results

The raw data from the pilot trial of on-line chlorine analyzers and the bench chlorine meter is given in Table C-1 and plotted in Figure C-4 located in Appendix C. The results are tabulated in Table 4-3. The two most accurate meters based on R^2, absolute error, and standard deviation when compared to the bench chlorine meter are the HACH CL17 and the Endress & Hauser.

TABLE 4-3 Summary of bench versus on-line analyzers

Chlorine Analyzer	Test duration (days)	Bench samples taken (#)	R^2 bench vs. on-line	Absolute error vs. bench (mg/L)	Standard deviation vs. bench (mg/L)
ProMinent	131	83	0.856	0.17	0.19
W & T Depolox 3+	131	88	0.898	0.18	0.17
Swan FAM Trides	131	91	0.869	0.24	0.23
HACH CL17	131	82	0.999	0.04	0.02
Endress & Hauser	100	64	0.981	0.10	0.07

Figure 4-4 compares the on-line trends for the two best meters (HACH and E&H) and the worst (Swan) over a three day span. The initial rise at the beginning is due to the depleted tank being slowly filled with chlorinated water from the Rossdale WTP Filter #5. At just after 6 AM on June 28/01, the chlorinated feed was stopped and the residual began to steadily decline for all three analyzers. Both the HACH and E & H analyzers closely matched each other, while the Swan analyzer read too high at the higher residuals and too low at the lower residuals.

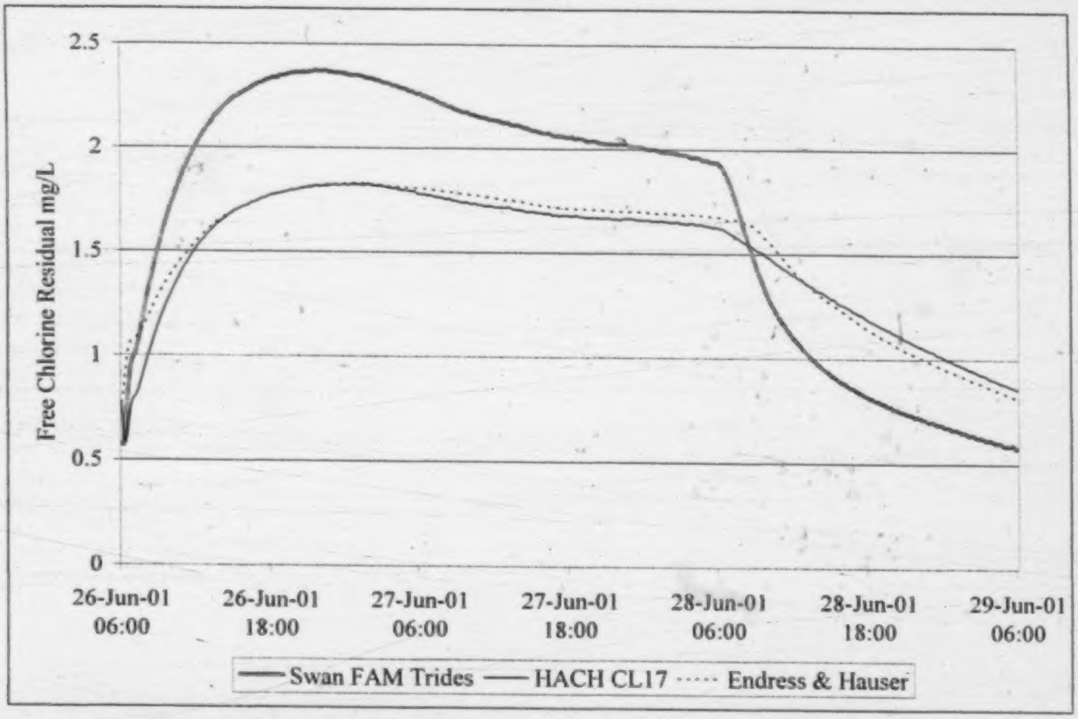


FIGURE 4-4 Three days of historical data from SCADA for the Swan, HACH, and Endress and Hauser free chlorine analyzers

In addition to performance, there were several other important parameters of concern: ability to run unattended, cost of the meter, cost of operation and maintenance, time and skill level necessary to operate and maintain the meter, compatibility with control options and remote communication methods.

Four of the five meters had a cost within two thousand dollars of each other, making it less important in meter selection. Recommended maintenance of the meters varied from 45 minutes per week to 1 hour per month. The colorimetric DPD meter had higher costs due to the consumables it required but this was balanced by its low maintenance requirement. Maintenance requirements vary depending on the type of meter and between manufacturers. The colorimetric meter requires chemical replacement once per month, sample cell cleaning every 1 - 4 months and tubing replacement once per year. The amperometric meters require replacement of electrolyte every 6-18 months and membrane replacement every 12 months or longer. All of these tasks require a minimum skill level to perform. The cost of the analyzer, its installation costs, ongoing operating cost, and annual life cycle costs were estimated in Table C-2 in Appendix C (Penny, 2001).

In terms of calibration, the colorimetric analyzer is self calibrating, requiring no maintenance or time. The amperometric analyzers must be manually calibrated. Depending on the performance of the analyzers, calibration intervals varied from an initial calibration at the start of the trial to frequent recalibration. The calibration procedure can be initially confusing, and would require training or careful following of the instructions in the respective manuals.

All of the analyzers tested were capable of generating alarms that could be used to trigger automatic shut-down of other systems. This feature is useful to help prevent non-ideal water from leaving the water treatment plant. The analyzers were also compatible with typical control systems and remote communication equipment and so data can be easily transferred where needed.

The results from the on-line chlorine analyzer pilot test show that there are chlorine analyzers available in the market place that are capable of operating ten days and even longer without requiring any sort of calibration or other maintenance. In the case of the HACH CL17 analyzer, the duration of thirty days between probe cleaning (a straightforward procedure that plant operators could be easily trained to do) coupled with the accuracy of the analyzer makes it an ideal choice for unattended operation. The analyzer also generates an alarm when the probe requires cleaning but will continue to work effectively for some time after before it generates a probe failure alarm. This feature is also helpful for unattended operation if operators are not on site when the probe clean alarm activates.

As far as the remote communication system is concerned, the quickest to install and configure and likely the least costly solution appears to be the internet based system as shown in Figure 4-3. It can provide data not only to the central control center but also to any staff member who has an internet connection. Because this system integrates the RTU and communication functions in one package and does not require any additional communication infrastructure at the (remote) site, it is the least complex and could be supported by the local staff.

4.4 Conclusions

The challenges faced by small isolated water plants in Canada are significant and include a lack of manpower and technical expertise to operate and maintain plants, difficulty in accessing the plants during severe weather conditions, and water quality violations. The public health effects of improperly treated water can be serious and preventing such failure must be the highest water quality objective.

By using on-line monitoring equipment, remote communication, and SCADA systems, it is possible to have the plants run reliably unattended with monitoring and control from a centralized location. The impact of applying this technology to isolated plants is expected to improve the quality, consistency, and safety of water. However, the cost of installing and managing this technology, if done with traditional methods, can be prohibitively expensive for smaller plants.

The results from the pilot test of on-line chlorine analyzers show that they are capable of operating for much longer than ten days at a time without requiring attention. It was shown that both the colorimetric and amperometric based analyzers were capable of meeting accuracy requirements however not all brands of analyzers performed well. The results of the pilot test concluded that the colorimetric based analyzer was the overall best performing unit in terms of meeting the objectives.

The wide area SCADA system concept and centralized control center presented in this chapter provides smaller isolated water plants with many of the functions that larger plants take for granted. These include 24-hour monitoring, control, alarming, data logging, daily, monthly, and yearly report generation. As the number of remote plants being monitored increases, the costs to individual plants become more favourable because all plants would be sharing the costs of the common equipment and its support. Centralization also makes it convenient to bring technical expertise at a lower cost when required to small water plants to handle problems with water quality, operation, and optimization.

4.5 References

1. Armstrong, T. F., Prince, D. S., Stanley, S. J., Smith, D. W. 1996. Assessment of Drinking Water Quality in the Northern River Basin Study Area Syntheses Report. Northern River Basins Study Report No. 9. Edmonton, Alberta. 153 p.

2. Penny, M. 2001. A pilot study evaluation of on-line free chlorine analyzers for monitoring remotely located water plants. EPCOR Water Services internal report. Edmonton, Alberta.

3. Pollack, A.J., Chen, A.S.C., Haught, R.C., Goodrich, J.A. 1999. Options for Remote Monitoring and Control of Small Drinking Water Facilities. Columbus, Ohio, Battelle Press. 302 p.

4. Gotoh, K., Jacobs, J.K., Hosoda, S., Gerstberger, R.L. 1993. Instrumentation and Computer Integration of Water Utility Operations. Denver, CO. AWWARF and JWWA. 476 p.

18. Shariff, R., Cudrak, A., Stanley, S. 2001. Remote Monitoring and Operation of Isolated Facilities in Cold Regions. Proceedings, AWWA Annual Conference, Washington D.C., June 2001.

5. Shariff, R., Thomas, S. 2001. Using On-line Analyzers at Remote Locations. Proceedings, Western Canada Water and Wastewater Association, October 2001.

6. Shariff, R., Cudrak, A., Stachowski, W., Welz, R., Stanley, S. 2002. Centralized Remote Operation of Multiple Water and Wastewater Plants. Proceedings, AWWA IMTech Conference, Kansas City, Mo., April 2002.

7. Smith, D.W., Ryan, W.L., Heinke, G.W., Reed, S., Reid, B.H., Rogness, D., Kowal, R.J. 1986. Cold Climate Utilities Manual. Montreal, Quebec. Canadian Society for Civil Engineering.

8. USEPA (United States Environmental Protection Agency). 2001. FY2000 IB SDWIS/FED Factoids. <www.epa.gov/safewater/data/00factoids.pdf>

5.0 AUTOMATION AND UNATTENDED OPERATION OF THE E.L. SMITH WATER TREATMENT PLANT

5.1 Introduction

EPCOR owns and operates two conventional water treatment plants in Edmonton, Alberta, Canada each capable of producing over 250 ML/d. A philosophy of continuous improvement in operating the plants has led to a steady increase in overall efficiency and water quality over the past number of years. Investments in process optimization, process control and automation have been partly responsible for this.

Due to changing work priorities from conducting repetitive types of tasks to higher skill and more diverse tasks, and to help reduce night shift work, an initiative was put forward in 2000 to pilot test unattended operation of the E.L. Smith Water Treatment Plant for certain periods of time. This would free up some operator time and allow them to develop the multiple skills necessary, especially in the area of maintenance, to meet the future needs of the organization. In turn, this would also allow the maintenance staff to focus on the more sophisticated type of work. A skill-based pay structure is also part of this program and has been implemented.

To achieve unattended operation successfully, it was identified early on that not only technical issues but also people issues would have to be addressed (Shariff et al, 2001). This chapter presents EPCOR's experience in converting from on-site to off-site control a large conventional water treatment plant producing high quality water through coagulation, flocculation, sedimentation, filtration, disinfection, and water pumping facilities. The steps taken to achieve this goal, the challenges involved in implementation and the benefits realized are also described.

5.1.1 Scope

The major objectives of this project were:

- Identify and modify systems, procedures and schedules to allow reliable unattended operation of the E.L. Smith WTP.
- Conduct a pilot test of operating the E.L. Smith WTP plant from the Rossdale WTP control room between November 19th, 2000 and February 19th, 2001.
- During the pilot test period, conduct unattended operation for up to 6 hours at a time between the hours of 01:00 and 7:00 am.
- Identify and analyze all events during the pilot phase that adversely affect reliable unattended operations.
- Prepare a report on the results of the pilot project and submit to Alberta Environment with recommendations.
- If recommended to continue, develop a strategy for extending the duration of unattended operation and include as part of regular plant operation.

5.2 Overview of the E.L. Smith Water Treatment Plant

EPCOR owns and operates two water treatment plants in Edmonton, Alberta, Canada which serve approximately 800,000 people in the area. The two plants, namely the Rossdale WTP and the E.L. Smith WTP, draw water from the North Saskatchewan River.

5.2.1 Treatment Processes

Both plants utilize conventional water treatment processes including clarification (alum, polymer, powdered activated carbon), disinfection (free and combined chlorine), filtration (filter-aid polymer), pH adjustment (caustic soda), on-site storage and pumping. A process flow diagram of the E.L. Smith WTP is shown in Figure 5-1. The annual range of raw water quality parameters and chemical dosing is quite wide (see Table 5-1) and therefore, at certain times of the year, very quick response to changing conditions becomes a necessity in order to maintain the stringent in-house water quality guidelines.

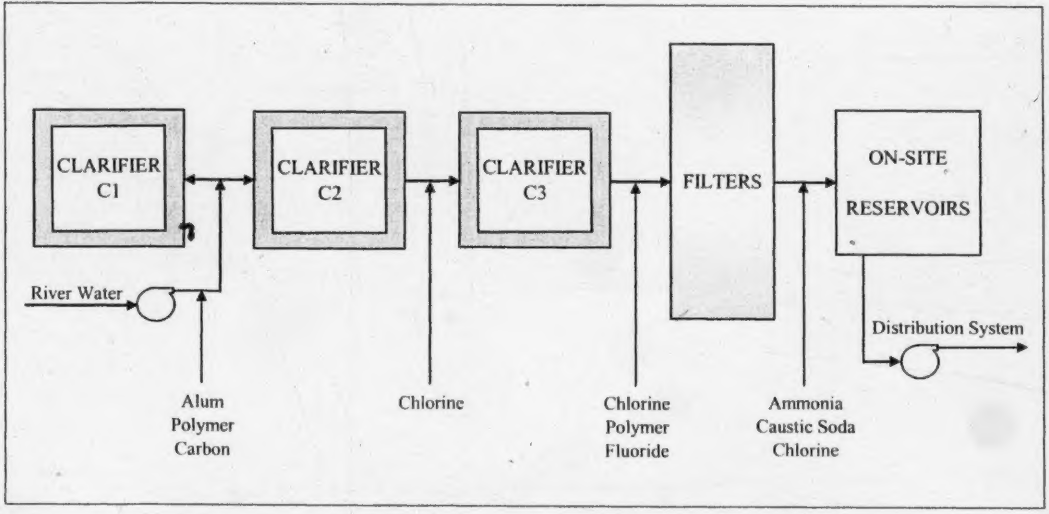

CLARIFIER
C1
CLARIFIER
C2
CLARIFIER
C3
FILTERS
ON-SITE
RESERVOIRS
River Water
Distribution System
Alum
Polymer
Carbon
Chlorine
Chlorine
Polymer
Fluoride
Ammonia
Caustic Soda
Chlorine

FIGURE 5-1 E.L. Smith WTP process flow diagram (2000)

TABLE 5-1 Range of raw water quality and chemical dosages at the E.L. Smith WTP

Raw water quality parameters; chemical dosages	Unit	Low	High	Average
Turbidity	NTU	1	> 2500	30
Colour	TCU	2	120	12
Temperature	deg C	0	25	8
Alum	mg/L	17	315	56
Polymer	mg/L	0.08	0.50	0.25
Powdered Activated Carbon*	mg/L	5	200	15
Chlorine	mg/L	2.25	3.80	2.90
Fluoride	mg/L	0.7	0.8	0.75
Caustic Soda	mg/L	2	60	11
Aqua Ammonia	mg/L	0.59	0.83	0.75

*Used during taste and odour events only

5.2.2 Control Systems

Prior to implementation of unattended operation at the E.L. Smith WTP, both plants were staffed twenty-four hours per day by operators on rotating 12-hour shifts. Each of the plants has a central control room from which remote monitoring and control of plant systems as well as the distribution system can be done. The SCADA systems themselves have been networked to integrate with the business side to the extent that real-time information is available instantly to anyone in the corporation, and in a similar graphical format as on the operator stations. A push towards improved efficiencies in the areas of power and chemical consumption along with tighter water quality regulations has put greater emphasis on automation, modeling, computer systems, information integration, and staff retraining.

The control systems for the water treatment plants and distribution operations are PLC-PC based and all three use the same SCADA software, Intellution® FIX-DMACS running on a Windows NT operating system. An Ethernet local area network is used to network the computers at each plant while dedicated high speed underground fibre optic cabling is used to network the plants together to form a wide area network. The ability to monitor all sites from any computer station is readily available. The two plants are approximately 24 km (18 km by river). Figure 5-2 illustrates the process control network at each plant and how the two are connected.

One of the key questions to be answered was whether unattended operation of the E.L. Smith WTP could be achieved without compromising finished water quality and supply to customers and without having excessive call-outs to the plant due to inadequate process control systems or general performance of equipment. Although EPCOR has had previous experience in remote operation of plants (Cochrane, Alberta – approximately 300 km away), that much smaller (10 ML/d) plant was designed from the ground up to operate automatically and unattended and did not have the wide raw water quality and chemical dosage range experienced at the E.L. Smith WTP. This was the main reason that the initial phase of unattended operation at the E.L. Smith WTP was conducted as a pilot project.

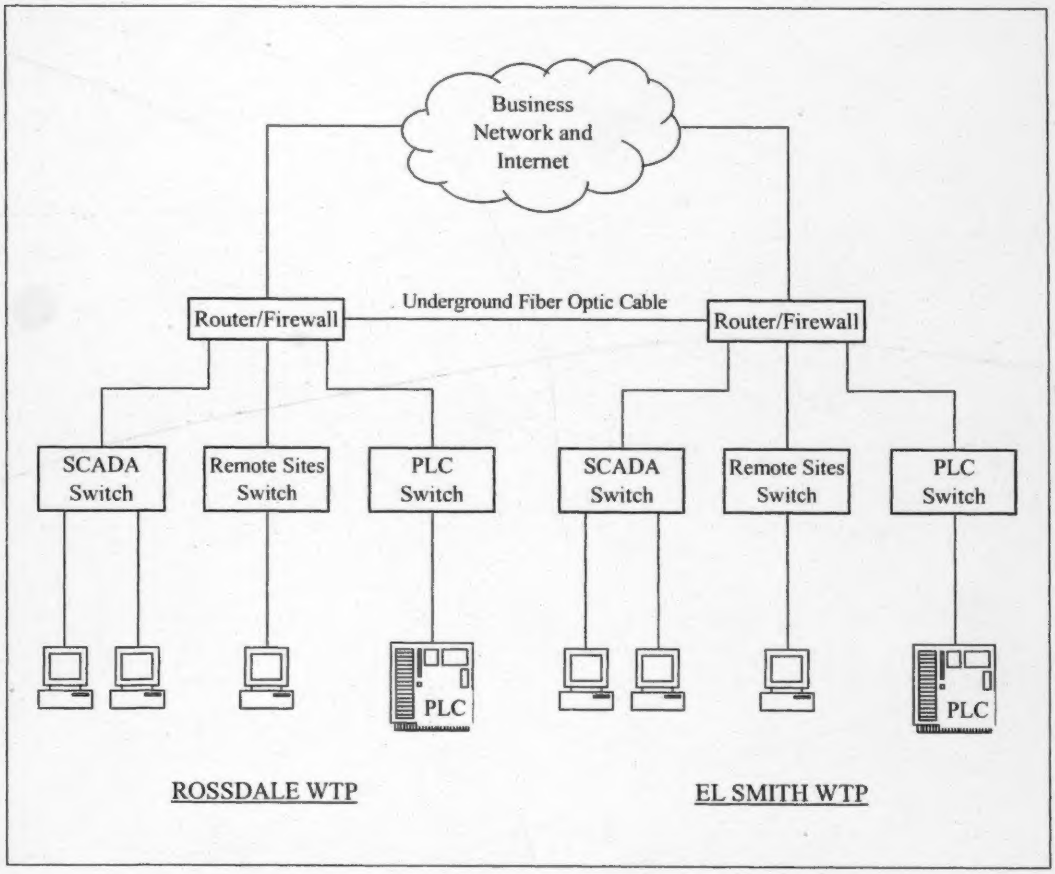

Business Network and Internet
Underground Fiber Optic Cable
Router/Firewall
Router/Firewall
SCADA Switch
Remote Sites Switch
PLC Switch
SCADA Switch
Remote Sites Switch
PLC Switch
PLC
PLC
ROSSDALE WTP
EL SMITH WTP

FIGURE 5-2 EPCOR Water Services control system layout

5.3 Methodology

Early into the project, it became apparent that there were various opinions, both negative and positive, as to the feasibility of the project and the amount of investment necessary to complete the yet to be determined modifications to the various systems. In addition, there was some scepticism about even being able to complete the necessary changes, as only six months of time was available.

In order to complete the project in time and within the available budget, it was clear that the most important item was the current state of automation at the plant followed by a list of recommendations for modifications. Based on the findings of this assessment, a time frame for completing the project could then be established.

A document entitled *"Policy on Automated/Unattended Operation of Surface Water Treatment Plants"* (10 State Standards, 1997) was found to be of great assistance and was used as a guideline in this project. It is recommended reading for anyone who is contemplating instituting unattended operation. The document can be ordered from the web site www.hes.org and includes a list of fifteen information/criteria items that should be included in an engineering report prior to commencing unattended operations. A brief summary of these items is given here:

1. Identify critical features to be monitored electronically. Provide a description of automatic plant shut-down controls. Dual or secondary alarms.
2. Provide automated monitoring of all critical functions. Provide automated plant shutdown on all major alarms. Prohibit automated start-up of plant after shutdown due to a major alarm. Provide control system with capability of challenge testing of major and minor alarms.
3. Provide capability of manual operation of all treatment plant equipment and process function.
4. Provide a plant flow diagram showing critical features, alarms, and automated controls.
5. Provide description of off-site control stations with ability to control operation.
6. Ensure a certified operator is available on "standby duty."
7. Inspect plant locally at least once per day.
8. Identify operator training requirements.
9. Provide an operations manual and emergency procedures.
10. Conduct a six month demonstration period to prove reliability of procedures, equipment and surveillance systems.
11. Develop a schedule for maintenance of critical equipment.

12. Ensure sufficient finished water storage is available to meet CT requirements in the event of production interruption.
13. Provide sufficient staffing to operate and maintain all aspects of the treatment plant.
14. Conduct weekly checks on communication and control system to ensure reliability.
15. Ensure provision is made for adequate security of the treatment facility. Incorporate intrusion alarms.

With the above in mind, the following was identified as functions and work that would be the required ingredients for a successful implementation of unattended operation of the E.L. Smith WTP.

Implementation Committee

An implementation committee was formed early on in the project. The function of the committee was to address issues related not only to technical items but also shift schedule and operator job function changes, training requirements, manpower requirements, setting clear protocols for such things as plant shutdowns/startups, and communicating information to the various departments. In essence, the implementation committee was empowered to review and as well, make final decisions on any item related to the project. Due to the fact that the nature of this project affected most departments in one way or another, the committee membership reflected this and included personnel from operations, maintenance, process services, network services, engineering, controls, safety, training, laboratory, and marketing.

Assessment of Systems

An assessment of plant systems as shown in Table 5-2 was done to determine the current level of automation, redundancy, and remote monitoring and control.

TABLE 5-2 **Plant systems assessment list**

Chemical feed systems	Alum, aqua ammonia, polymer, carbon, chlorine, fluoride, caustic soda
Power, air, fire	Electrical, instrument air, fire alarms, UPS, emergency power systems, availability of systems after power bumps through remote resets
Process and pumping	Raw water pumping, clarifier operation, filter operation, on-site finished water reservoirs and pumping
On-line analyzers	Availability and performance of pH, turbidity, particle count, colour, chorine residual, and fluoride residual analyzers
Auto-shutdown	Automated shutdown capability of equipment on major alarms
Control system	SCADA, remote communication
Security	Intrusion alarms, video surveillance

Operator Training, Shift changes, and Communication

Operator training was identified as an important aspect to the success of this project particularly with respect to operating systems solely from a remote site through a computer system. To improve the level of understanding for operators on current and newer systems to be deployed as a result of this project, the Training and Manuals Group conducted a review of the accuracy of the Operator Training Manual with the goal of updating critical sections and utilizing them to train operators.

A special sub-committee was set up to review the impact on operator work schedules and life-style as a result of unattended operation. The committee consisted of members from the plant operations staff and union representatives. The committee was also responsible for communicating with the rest of the operator staff and to recommend the best possible solution for operator schedules.

Accurate and timely communication to the internal staff, the Union, the media and the public at large was considered to be vital to the overall success of this project. A plan regarding communications was developed by the marketing and business development personnel.

Approval (license) to Operate

The E.L. Smith WTP Approval to Operate granted to EPCOR by Alberta Environment was reviewed in detail with the regulator to ensure that EPCOR would not inadvertently violate any of its requirements while conducting unattended operations. Some of the areas that were to be reviewed were related to the use of on-line analyzer readings as opposed to bench tests for regulatory reporting, remote operator certification level, reaction times, and protocols to be followed should failures occur.

Once the above mentioned functions had been reviewed and changes implemented, a two week trial run was planned to help identify any outstanding issues that needed addressing prior to commencing unattended operations.

5.4 Implementation

Following the completion of the various assessments, a large number of recommendations were produced and it became clear that not all recommendations could be implemented nor was it necessary to do so. To assist the members of the implementation committee in prioritizing the recommendations based on the overall objectives to be met and to ensure that the recommendations that do not get implemented do not adversely affect water quality or otherwise impart undue risk to water supply and overall safety, a straight forward and simple rating system was developed as shown in Table 5-3.

Once the recommendations had been prioritized, all the A* and A items required implementation. The work was completed through in-house resources as well as outside electrical and mechanical contractors. The various designs for the changes necessary, contract administration and supervision of the contractors were done by in-house staff.

The role of in-house expertise in many areas was vitally important to meeting the completion date of the project. A summary of the work that was done is described in the following sections.

TABLE 5-3 Rating of recommendations

Recommendation Rating	Implication
A*	Critical recommendation - must be implemented prior to onset of unattended operation. An example would include such things as remote control of filter operation or post-filter bypass; on-line chlorine or fluoride residual analyzers, security system related recommendation.
A	Highly desired functionality that needs to be implemented as soon as possible i.e. if not prior to onset of unattended operation then shortly thereafter. For example, remote resetting capability of the low lift pumps after a power bump; remote switching of chemical feed equipment due to failure. These types of occurrences, if not alleviated remotely, will likely require a plant shutdown and subsequent operator and/or maintenance call-out.
B	Desirable improvement or functionality to be implemented in the long run especially if the duration of unattended operation is increased or occurs during worsening raw water conditions. The recommendation would improve the overall system efficiency and performance; reduce risk of failure; improve water quality beyond current targets; further improve security and so on. Some of the recommendations falling in the B category may already have been included in the company's long-term capital improvement program. Examples: a new polymer feed system; additional redundant analyzers; advanced process control techniques.
C	Likely will not be implemented at all unless additional justification can be provided.

5.4.1 Chemical Feed Systems

The desired minimum level of automation for each chemical feed was automatic flow pacing to the incoming water flow rate based on a given dose set-point. The ability to switch to a backup system remotely was also a preference. Based on this, the following changes were made:

- Alum – improve flow control and remote control of feed system.

- Aqua Ammonia – install remotely controllable isolation valves.
- Chlorine – extensive upgrades to the feed system required. New mass flow meters added, remote switchover capability for chlorinators and eductors and various piping redesign, analog leak detector sensor installed to help gauge severity of leaks, and upgraded automatic flow, dose and residual controls programmed.
- Polymer – add remote batch initiation switches, remotely controllable service water isolation valves, and wire additional alarms to the SCADA system.
- Caustic Soda – install remotely controllable isolation valves.

5.4.2 Electrical, UPS, Power, Fire alarms

- When intermittent power bumps occur, much of the equipment installed at the plant requires resetting locally before the affected equipment can be restarted. Therefore, remote resets which allow resetting of the equipment from the SCADA system were desirable and were installed for the low-lift and high-lift pumps, clarifier recirculators and rakes.
- UPS power replenished by the onsite emergency generator was connected to the SCADA local and wide area network communication equipment.
- Upgraded SCADA screens for the power system and other electrical changes were prepared.
- Connection of fire alarms to the plant SCADA system.

5.4.3 Filters

The existing filter controls were outdated and required extensive rework in terms of control hardware (PLC's) and control programming. This had been identified earlier during the year. The implementation committee recommended and helped design a highly automated system which gave full remote control capability of individual filters to the operator via the SCADA system.

5.4.4 On-line Analyzers

An extensive array of on-line analyzers already existed at the plants. Key additional analyzers installed were new fluoride residual analyzers that had been tested for accuracy by the plants on-line analyzer committee, and additional chlorine analyzers for improved control and as well, redundant analyzers were bought and installed. Sample line designs and changes were also done. An on-line QA/QC web based database showing statistical process control charts for each analyzer along with procedures for maintaining the analyzers was also developed and implemented.

5.4.5 Automatic Shutdown Systems

To further protect finished water quality, existing automatic shutdown systems were enhanced and new ones were developed and implemented. The systems were designed to activate even when remote communication was lost or if the main SCADA computer crashed. All individual filter effluent quality was protected by an automatic filter shutdown system which activated whenever the effluent particle counts or turbidity exceeded a preset value. Shutdown systems were also added for protecting the on-site reservoir finished water quality with automatic closure of valves based on out of range values of chlorine residual, fluoride residual, pH, and turbidity.

5.4.6 SCADA Systems

The E.L. Smith WTP SCADA system host can be accessed from the Rossdale control room via an existing high-speed redundant dedicated fibre optic cable network. Additional changes included:

- Installation of additional operator stations at the Rossdale control center.
- Installation of a backup E.L. Smith SCADA host computer at the Rossdale control center which could be activated by an operator during failures. To provide this capability, the E.L. Smith PLC communication network required conversion from a

proprietary and less compatible system to a more modern and open Ethernet based system that was compatible with the existing high speed fibre optic link between the plants.

- Backup communication path between control rooms.
- Additional operator screens to aid with monitoring the plant systems more quickly/efficiently. An example of a new screen created specifically for unattended operations is a comprehensive graphic of the E.L. Smith plant (shown in Figure D-1 in Appendix D) that shows important statuses of most systems, alarms, and important control set-points.

5.4.7 Security Systems

An extensive review of the security system was performed and a large number of recommendations were made of which a few are mentioned here:

- Complete review of all doors including re-defining the function of each door and re-keying. Upgrades included repairs to all doors and hatches, and installation of door locks.
- Improved intrusion detection capability by installing additional door alarms and motion sensors and repairing existing alarms.
- Repairs to the fence, new signage, and control of the main gate from the SCADA system.
- Installation of networking equipment to allow real-time viewing and control of all security cameras from the Rossdale control room computers. A tape system for recording video from all cameras.
- Establishing procedures for routine checking of various security systems.
- Cell phones for shift charge operators.

5.4.8 Training

A major effort was undertaken to ensure that the operations manuals were up to date and that the operators were trained on the procedures. To accomplish this, a web based operations manual was set up and as well, a practical training program for the operators with written exams was implemented. For complex systems such as filter controls, simulation software was used to aid in the training process.

5.4.9 Communication

A communication plan was prepared to ensure accurate information was being tran~~sferred in~~ a timely manner. Several methods were used:

- Regular newsletters were prepared and attached with the employee pay-cheques. The newsletters (see example in Figure D-2 in Appendix D) were prepared in a question and answer format and covered a variety of issues such as time frames, reasons for testing unattended operation, shift schedule impact, benefits to staff, technical information, risks involved and how they would be mitigated and so on. A example
- Information was also presented on the company intranet web site.
- Regular meetings with the operations staff were held.
- Implementation committee meetings were held.
- Updates were provided to corporate staff during presentations by the president of EPCOR Water Services.
- Updates and presentations were provided to the regional customers during regularly scheduled meetings.
- An information pamphlet was prepared for release to the media if required.

5.4.10 Shift Changes

A separate committee was established to review the impact of unattended operation on operator's staff lifestyles. Prior to unattended operations, the plants were operated on two twelve-hour shifts – one starting at 7 am and ending at 7 pm, and the second starting at 7 pm and ending at 7 am. The shift committee worked very closely with the operators and a consensus was reached with the addition of a new shift between 2 pm and 2 am.

5.4.11 Approval to Operate

The Approval to Operate (formerly known as License to Operate) is prepared by Alberta Environment (AEnv) and lists all the requirements that must be met by the utility in operating its water treatment plants. Discussions were held with the approvals engineer which led to the suggestion by the engineer that the unattended operation of the E.L. Smith WTP should initially be done as pilot project. As long as all the required monitoring and reporting criteria as stated in the approval were not being compromised, no amendments to the Approval would be required. A report following termination of the pilot project would be prepared and after review, a decision would be made as to whether any amendments would be required in the future.

5.4.12 Departure/Security/Alarm Response Procedures

- A check-list was prepared for the operator to review every time the plant was left unattended. It included items such as checking of equipment to ensure it was available for control remotely to ensuring that all the security systems were left in a functional order. On any given night, unattended operation would not proceed if key systems were not working, could not be monitored or controlled from the SCADA system, or if challenging treatment conditions occurred.
- A policy was outlined regarding plant startup after an unscheduled shutdown. During unattended operation, it was stated that the plant could be restarted and all systems activated remotely with the exception of the on-site finished water reservoir inlet valves. These valves could only be opened after an operator had conducted a site visit and confirmed that all was in order.

5.4.13 Electronic Log Books

Electronic log books became a necessity as personnel began to monitor the plants remotely. Web based log books were developed in-house and these were made available to any user through the local intranet server.

5.4.14 Pilot Trial

Once all systems were considered ready, a 2-week trial run of unattended operation was conducted. During the trial phase, operators were to stay on-site in the control room for the duration and only monitor the plant through the SCADA system. Any events that required attention would be responded to through the SCADA system only unless it was not possible to alleviate the problem and the event could cause a major issue. The purpose of the trial run was to determine if there were any outstanding issues that had not been identified in the earlier assessments. The trial phase identified a couple of items that required attention during the trial phase:

- The post filter automatic bypass system tended to activate intermittently. It was determined that very short lived spikes from the chlorine and particle count analyzers were triggering the closure of the finished water inlet valves. The programming was adjusted accordingly.
- Some of the door alarms switches began to malfunction and required replacements.
- A few minor computer related glitches required attention.

Once the trial run was completed, the unattended operation pilot project officially began starting November 19th, 2000 and ending on February 19th, 2001.

5.5 Results and Discussion

The overall results from the pilot trial phase of unattended operations of the E.L. Smith WTP were very encouraging. The operations staff soon became comfortable in monitoring and controlling all equipment remotely including washing of the filters, making chemical adjustments, and turning pumps on and off.

Since it was required for the charge operator (most experienced operator) to drive for thirty minutes or so to the Rossdale plant at 01:30 am to complete his/her shift whenever unattended operation was being conducted, some of the operators were not too keen on this as it meant driving late and in some cases, a longer drive home.

A few call-outs were made during the trial phase. One was due to an intermittent faulty analyzer reading triggering the post filter bypass, and the second due to a suspicion that a small chemical leak had started and was entering the on-site sanitary tank as detected by a high pH reading. In both cases, improvements were made to reduce the chance of the problem from occurring again. There had also been intermittent problems with the video camera system. In summary, events, call-outs, or cancellations during the 3 month trial included:

- High pH reading in Sanitary Tank – valve in boiler room leaking.
- Post filter bypass activated due to faulty particle count sensor.
- UPS power failure – affected SCADA and Filter PLC – unattended operations was cancelled for one night.
- Process problems after plant shutdown – unattended operations was cancelled for one night.
- Motion Sensor in the Chemical Feed building activated but nothing could be viewed on the camera. The Highlifts were shut off and the police were called. Nothing was found. A faulty / dirty motion sensor or flickering of lights may have caused the alarm.

5.5.1 Other Observations:

- The use of the intranet for such things as the log books, operations manual, and QA/QC database for on-line analyzers has also had the effect of improving communication between the different areas including the operations staff at the two plants and between the maintenance and operations staff. The web based approach provides a single source of information for all staff at any time and its use is expected to grow.

- The presence of the E.L. Smith WTP operators at the other plant on a regular basis has also improved communication, teamwork, and learning of other systems.
- Due to the fact that the E.L. Smith plant is now operated unattended, all new installations of equipment and systems must meet a minimum standard for automation. This has affected engineering designs and projects that are implemented at that plant.
- The criticality of repair for equipment has also been affected somewhat. There is now an increased urgency to have equipment repaired much sooner for such things as on-line analyzers, security systems, controls, and any equipment that cannot be operated remotely due to a break-down. Failure to do so could mean that unattended operation may not be possible on that day thereby requiring an after hours operator at a premium rate. The operations staff are now more proactive in identifying problems and conveying them to the maintenance staff and ensuring that they understand the priority of a given piece of equipment. Backup systems can no longer be left unavailable for extended periods due to a breakdown.
- The experience in operating a sophisticated plant such as the E.L. Smith WTP from a remote location has given not only the operations staff a higher level of confidence but also the other affected groups as well including the management staff. It is a milestone for the company and it has provided an understanding of what is required and what is important when it comes to unattended operation. This experience will help with future endeavours in operating out of town plants in a reliable and cost effective manner.

5.5.2 Post Implementation Review

Following the pilot trial phase which ended on February 19th, 2001, a review was conducted. Based on the success of the trial, it was determined that to make it more effective, the duration of unattended operations needed to be extended to 12-hours at a time which is the current length of operator shifts.

A report on the pilot trial which included the proposed new duration of unattended operation was presented to AEnv. Upon approval from AEnv, EPCOR Water Services implemented Phase II of the project and unattended operation (what is now commonly referred to as remote operations) of the E.L. Smith WTP was officially formalized and made part of normal plant operations beginning late November, 2001. The latest synopsis of unattended operations of the E.L. Smith WTP is very positive and very few minor incidents have been encountered.

In Phase II, system improvements that were implemented were designed to improve security, water quality measurements, and power recoverability. Briefly, they included:

- Additional motion sensors and door alarm contacts in the clarifier, chemical feed, and the on-site treated water reservoir buildings.
- Additional cameras including an external camera overseeing most of the plant site.
- Improved system for controlling the E.L. Smith camera from Rossdale and for recording the video from each camera for future viewing.
- An on-line colour meter for raw water and a Streaming Current Detector (SCD) meter.
- Improved automatic power recoverability system for Highlift pump #4 (one of two large finished water pumps) to help ensure that customers are provided with adequate water pressure and supply as soon as possible after power outages.
- Various control and redundancy improvements.

5.6 Conclusions

This chapter has presented EPCOR's experience with converting one of its two conventional water treatment plants from a fully staffed operation to unattended operation for periods of time. The project was successful and has provided the company and its staff with valuable experience and confidence in its ability to reliably operate treatment facilities with multiple processes that have highly variable raw water conditions.

The time frame required and capital investment necessary to convert a plant to unattended operation depends on the type of treatment and its present state of automation. The E.L. Smith WTP was not originally designed with unattended operation in mind, but some of the newer systems had been designed and operated with automation in mind over the past several years. This helped to speed up the conversion to unattended operation not only due to fewer systems requiring changes but more significantly due to the availability and use of experience that the in-house staff had gained over the years from designing and operating automated systems.

Finally, it is recommended that utilities that are considering unattended operation for their plants must conduct a pilot phase approach as described in this document. It allows the utility to assess what works and what requires changes. It also helps the staff to become acquainted and comfortable with the new method of operation.

5.7 References

1. 10 State Standards and Ontario, Recommended Standards for Water Works (1997), Policy on Automation/Unattended Operation of Surface Water Treatment Plants, Health Education Services, Albany, N.Y.

2. Shariff, R., Welz, R., Stanley, S. J., Stachowski, W., and Corscadden, R. (2001), Automation and Unattended Operation of Large Water Plants, Proceedings, AWWA IMTech Conference, Atlanta, Georgia, April 8-11.

6.0 CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE STUDY

6.1 Conclusions

The overall objective of this thesis was to develop appropriate automation techniques for drinking water treatment plants to improve water quality and consistency and costs. The techniques were to address a full spectrum of plants from small isolated production facilities that require only basic treatment to larger more sophisticated plants that must deal with difficult treatment challenges and increasing costs of production. To this end, the thesis was focused on two major areas of automation: advanced control techniques and remote monitoring techniques. These were developed in four separate study sections:

1. Development of ANN models for a full-scale lime softening process at the Rossdale WTP.
2. Development of computer process control methods for integrating ANN models into a SCADA system.
3. Development of reliable and cost effective automation and remote monitoring methods for small remotely located and isolated water systems.
4. Implementing unattended operation of a large conventional water treatment facility namely the E.L. Smith WTP.

It was found that artificial neural network (ANN) based models for the Rossdale WTP lime softening process yielded much more accurate results compared to actual plant performance then the USEPA WTP modeling software. For example, the USEPA model was only able to predict total hardness to an accuracy of 15 mg/L on average with gross errors reaching as high as 70 mg/L. The ANN models on the other hand predicted to an accuracy of within 0.5 mg/L on average with gross errors reaching only 9 mg/L. In addition, the average lime dose accuracy using the ANN model was within 0.5 mg/L. The ANN models could also be useful at other plants with similar processes as the architecture and methodology developed in this research can be re-applied thereby greatly reducing the time required to develop the models. Furthermore, integration of ANN, model-based control schemes, and real-time control systems to achieve advanced control is a viable solution for water treatment processes where a higher degree of control is required.

For simpler plants, particularly small isolated facilities, the use of on-line monitoring, remote communication, and SCADA systems can provide reliable unattended operation with monitoring and control from a centralized location. The impact of applying this technology to isolated plants is expected to improve the quality, consistency, and safety of water.

For larger, more sophisticated plants with challenging raw water conditions such as the E.L. Smith WTP, implementing unattended operation is a much more involved process and both technology and people issues must be addressed. The success of this project was largely due to an empowered Implementation Committee that was formed early in the project to manage both technology and people issues. The Implementation Committee also created sub-committees as necessary to review specific areas (e.g. shift schedules). Through this process, all stake-holder's input was received and operator buy-in and acceptance was achieved which helped to smooth out tensions once unattended operation was started. Other benefits included an increased level of confidence in managing plants remotely for operations staff, other affected groups and the management staff. The experience gained has helped EPCOR with future endeavours in operating out of town plants in a reliable and cost effective manner. On the technology side, it is expected that advanced controls will likely be installed first in larger more sophisticated plants in the near future.

Other findings from this research were:

1. It was illustrated that an accurate inferential or virtual sensor for predicting the alum clarifier effluent pH can be developed with ANN. It was developed in this study to serve as an input for the lime ANN model when conducting "what if"

scenarios. It was also shown that the virtual sensor can become part of an actively running control loop where real-time predictions are required.

2. To further improve the accuracy of the softening ANN models and to make the accuracies of the forward and inverse models match more closely, other relevant input parameters such as solids content in the clarifier and sludge recycle flow rates need to be identified and evaluated. However, it may be difficult or even impossible to obtain reliable data for all the desired input parameters (as was the case in this study).
3. A vital step towards the implementation of advanced controls is the successful integration of ANN based models with plant real-time process control systems. This can be done by first choosing a control scheme such as the ideal model-based control scheme or the more sophisticated IMC (internal model control) scheme. Additional requirements for real-time integration include a SCADA system, on-line instrumentation, and an ANN interface.
4. It was shown for the lime softening process models that once the ANN models are integrated with real-time control systems, continuous predictions can be made and that these can be used for automatic control of lime dosages.
5. The results from the pilot test of on-line chlorine analyzers showed that they are capable of operating for much greater than ten days at a time without requiring attention (the target of ten days was chosen to make sure that the analyzers could be depended upon should site visits to the plants be reduced to every 7 to 10 days). It was shown that both the colorimetric and amperometric based analyzers were capable of meeting accuracy requirements however not all brands of analyzers performed well. The results of the pilot test concluded that the colorimetric based analyzer was the overall best performing unit in terms of meeting the objectives.
6. The wide area SCADA system and centralized control center concept was shown to be capable of providing smaller isolated water plants with many of the functions that larger plants take for granted. These include 24-hour monitoring, control, alarming, data logging, and daily, monthly, and yearly report generation. As the number of remote plants being monitored increases, the costs to individual

plants are more favourable because all plants would be sharing the costs of the common equipment and its support.

7. The time frame required and capital investment necessary to convert a plant to unattended operation depends on the type of treatment and its present state of automation.
8. The use of contemporary automation techniques to treat water does increase its safety and consistency when compared to the traditional reactionary method of treating water.

Finally, it can be concluded that as utilities face increased pressures to manage costs and maintain quality, the degree of control required to run the plants efficiently will increase too, which will likely lead to an increase in the use of automation.

6.2 Recommendations for Future Study

The recommendations for future study that are made here are based on observations and results achieved during the study phase.

1. Maintaining reliability and accuracy of the ANN control system with time is an important area for more research. Specifically, out-of-bound input detection, error detection and data handling techniques, model drift detection methods, model robustness, and long-term/short-term ANN modeling systems are areas that need to be investigated. The feasibility and practicality of a system that would automatically update ANN models on-line needs to be researched further as well.

2. The ability to model processes more accurately and affordably improves the chances of implementing plant-wide control and management systems. These are systems that link multiple models (process, energy use, production capability, demand forecasting, quality, costs, and so on) into a constraint based decision making system. More research is required in this area to help water treatment

facilities attain plant-wide control to reap important benefits in water quality and consistency and costs of production.

3. Development of more on-line inferential sensors for the water treatment process would be very useful for validating existing on-line instruments, for use in control schemes, and for producing real-time predictions for parameters whose values are only determined infrequently and not at the time of sampling.

4. For remote monitoring of plants, reliable, affordable and low maintenance on-line analyzers do exist for certain parameters but more work is required for others such as colour.

5. To improve the availability of the communication systems used for remote monitoring, redundant links that can be quickly and easily activated during failures either automatically or by the operations staff through their computer systems need to be developed.

APPENDIX A Lime Softening Clarifier Modeling with Artificial Neural Networks

TABLE A-1 Water quality guidelines for EPCOR plants in Edmonton (1997 version)

SUMMARY OF AQUALTA, EDMONTON WATER QUALITY STANDARDS

Water Quality Parameter	Objective/Warning Limit		Control Limit		Approval (1) Requirement	Aqualta (2) Shutdown Levels
	Min	Max	Min	Max		
Turbidity						
Clarifier Effluents		3		10		
Individual Filter		0.1		0.3	≤1.0 (≤2.0) (3)	>0.5
Combined Effluent		0.1		0.2	<0.8 (4)	>0.5
High Lift Pumps		0.1		0.3		>0.5
Distribution System				1	<5.0	
Lime Waste at ELS					<10.0	>10.0
Particle Counts						
Individual Filter (<5C)		30		50		50
Combined Effluent (<5C)		50		70		80
Individual Filter (>5C)		30		70		70
Combined Effluent (>5C)		100		150		200
Combined Chlorine						
Pre-Reservoir	1.8	2.3	1.7	2.4		<1.6 or >2.5
High Lift Pumps	1.8	2.3	1.7	2.4	≥0.5 and ≤2.5	<1.6 or >2.5
Field Reservoirs			1.5	2.4	≥1.0 and ≤2.5	<1.0 or >2.5
Distribution System			1.0	2.4	≥0.5 and ≤2.5	<0.5 or >2.5
Log Removal (Giardia)						
Hourly Average per Plant	3.2		3.1		> 3.0	<3.1
Bacteria (After Filtration)						
HPC/1 ml		10		500		
Total Coliforms/100 ml		0		0	<10 in 1st sample	>0 in 2nd sample
Fecal Coliforms/100 ml		0		0	0	>0
pH						
High Lift Pumps	8.0	8.5	7.5	8.7	>6.5 and <9.0	<6.5 or >9.0
Post Filter	8.0	8.5	7.5	8.7		<7.5 or >9.0
Lime Waste at ELS					>6.0 and <9.0	<6.0 or >9.0
Fluoride						
Daily @ HLP	0.95	1.05	0.9	1.1	0.8 - 1.2	<0.9 or >1.1
Monthly @ HLP	0.95	1.05	0.9	1.1	0.9 - 1.1	<0.9 or >1.1
Volatile Organics						
Raw						>0.100
Post Filter		0.005		0.010		>0.020
Trihalomethanes						
Post Filter		0.02		0.05	<0.1	>0.1
Colour (TCU)						
@ HLP		2		5	15	>10
Taste and Odour						
Post Filter	Inoffensive		Inoffensive		Inoffensive	
Total Hardness						
@ HLP	125	135	90	145		
CCPP	-3.0	3.0	-5.0	5.0		
Conductivity (umhos/cm)				300		Anytime contamination is suspected.

- parameters in log books exceeding the exceeding warning range should be circled.

(1) Approval Requirements
- daily average values, unless otherwise indicated
- according to Alberta Environment Approval, parameters outside these limits represent violations of the approval to operate.

(2) SHUT DOWN
- instantaneous values.
- See Emergency Manual for additional details on shutdown criteria.

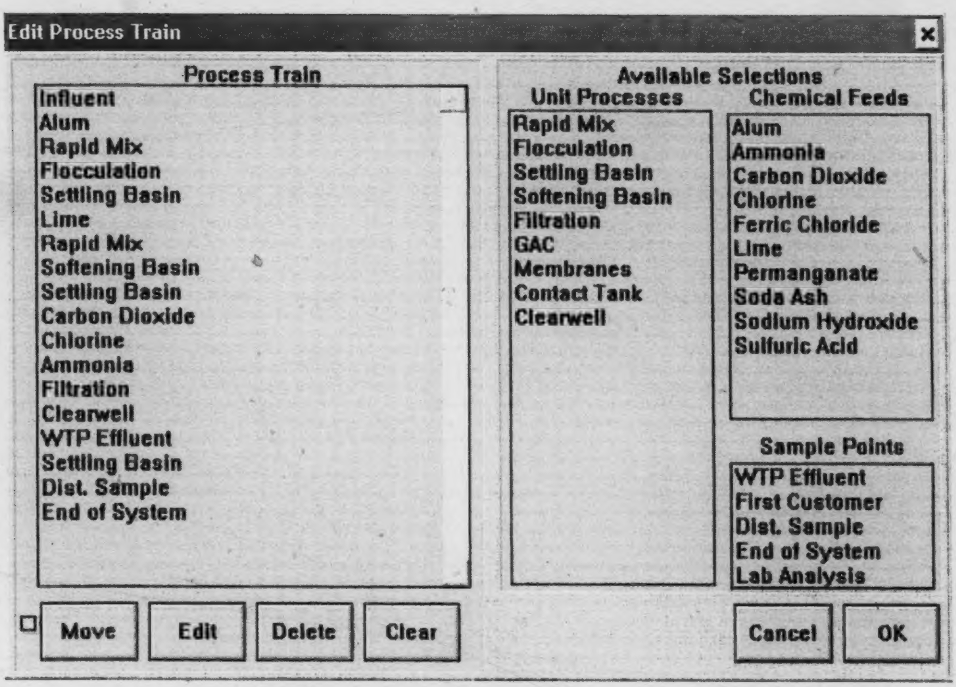
(3) Individual filter turbidity shall be less than 1 NTU 99% of the time(daily), and never exceeding 2 NTU.
Combined filter turbidity shall not exceed 1 NTU if raw > 2.5 NTU, 0.8 NTU if raw 1.6-2.5 NTU or 50% of raw if < 1.6 NTU.

(4) Individual filter turbidity >5 NTU, shutdown HLP's and notify the Plant Director for further action.

- all units are mg/L unless listed separately, changes from last version highlighted

T. Wetmore / R. Welz
June 9, 1997

File: p:\aqsa\rwelz\WQ_STD.XLS



Process Train

- Influent
- Alum
- Rapid Mix
- Flocculation
- Settling Basin
- Lime
- Rapid Mix
- Softening Basin
- Settling Basin
- Carbon Dioxide
- Chlorine
- Ammonia
- Filtration
- Clearwell
- WTP Effluent
- Settling Basin
- Dist. Sample
- End of System

Available Selections

Unit Processes

- Rapid Mix
- Flocculation
- Settling Basin
- Softening Basin
- Filtration
- GAC
- Membranes
- Contact Tank
- Clearwell

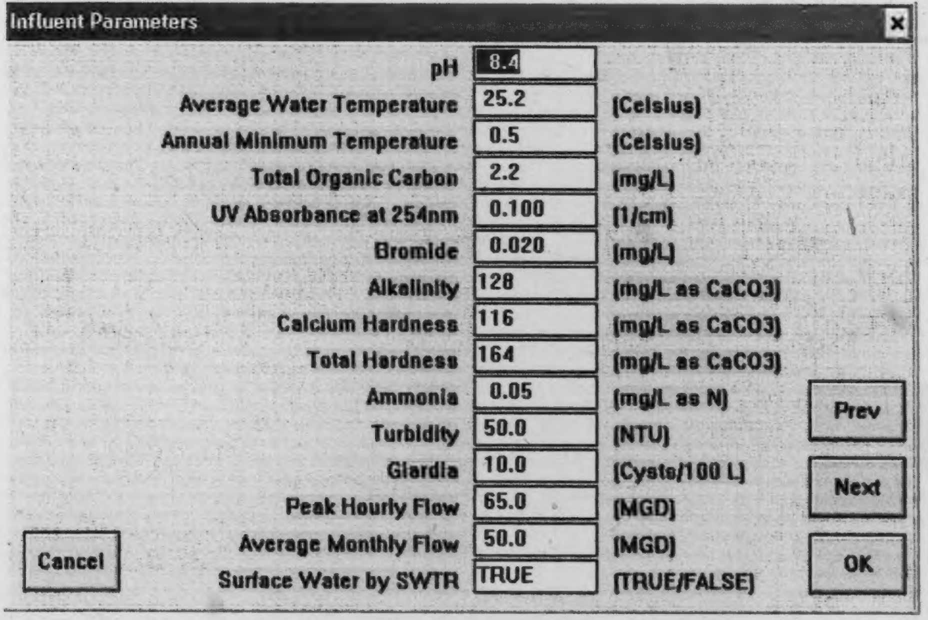
Chemical Feeds

- Alum
- Ammonia
- Carbon Dioxide
- Chlorine
- Ferric Chloride
- Lime
- Permanganate
- Soda Ash
- Sodium Hydroxide
- Sulfuric Acid

Sample Points

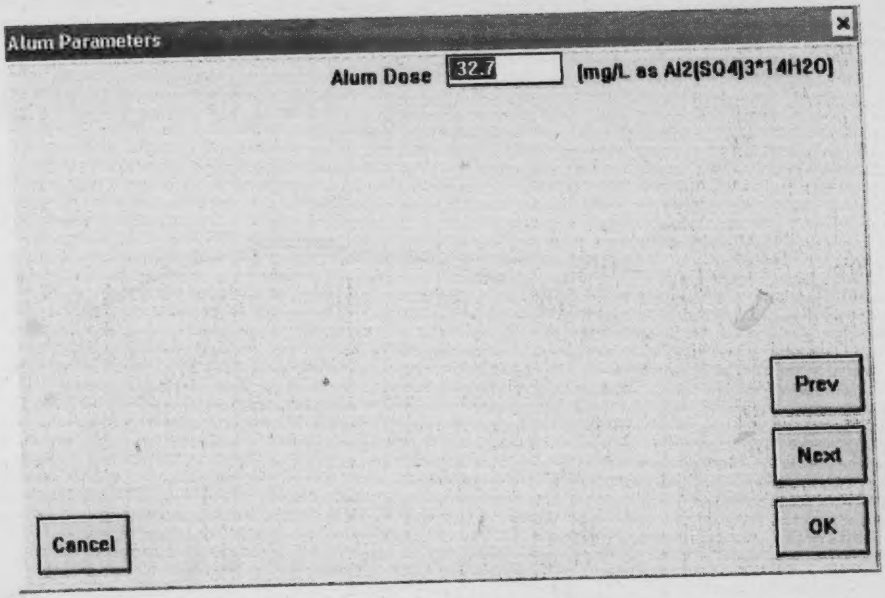
- WTP Effluent
- First Customer
- Dist. Sample
- End of System
- Lab Analysis

FIGURE A-1 USEPA WTP modeling software input screen 1



pH	8.4	
Average Water Temperature	25.2	(Celsius)
Annual Minimum Temperature	0.5	(Celsius)
Total Organic Carbon	2.2	(mg/L)
UV Absorbance at 254nm	0.100	(1/cm)
Bromide	0.020	(mg/L)
Alkalinity	128	(mg/L as CaCO3)
Calcium Hardness	116	(mg/L as CaCO3)
Total Hardness	164	(mg/L as CaCO3)
Ammonia	0.05	(mg/L as N)
Turbidity	50.0	(NTU)
Giardia	10.0	(Cysts/100 L)
Peak Hourly Flow	65.0	(MGD)
Average Monthly Flow	50.0	(MGD)
Surface Water by SWTR	TRUE	(TRUE/FALSE)

FIGURE A-2 USEPA WTP modeling software input screen 2

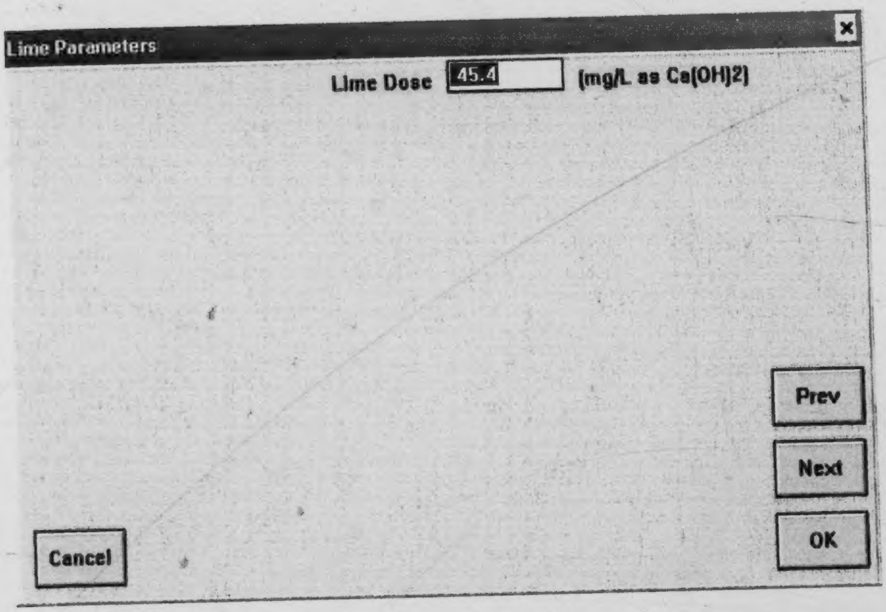


Alum Parameters

Alum Dose 32.7 (mg/L as Al2(SO4)3*14H2O)

Prev
Next
OK
Cancel

FIGURE A-3 USEPA WTP modeling software input screen 3

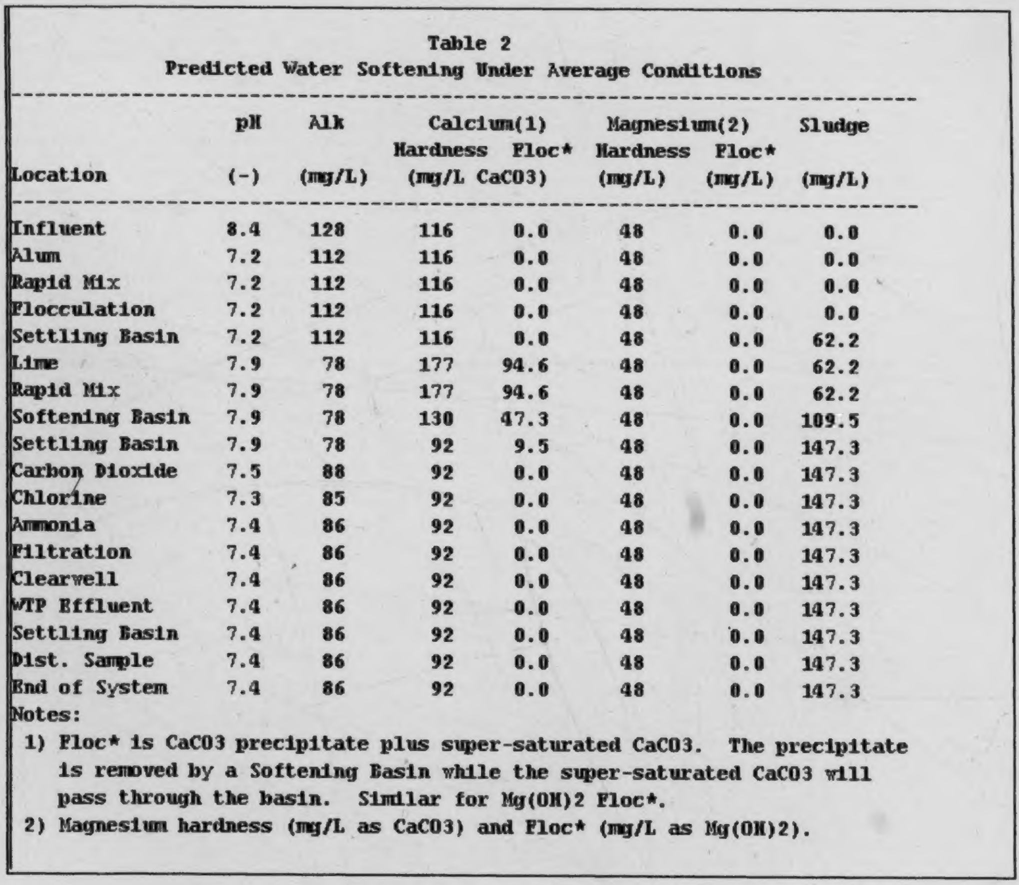


Lime Parameters

Lime Dose 45.4 (mg/L as Ca(OH)2)

Prev
Next
OK
Cancel

FIGURE A-4 USEPA WTP modeling software input screen 4



```
                              Table 2
            Predicted Water Softening Under Average Conditions
------------------------------------------------------------------------
                  pH     Alk       Calcium(1)        Magnesium(2)   Sludge
                               Hardness   Floc*  Hardness   Floc*
Location          (-)   (mg/L)   (mg/L CaCO3)     (mg/L)   (mg/L)  (mg/L)
------------------------------------------------------------------------
Influent          8.4    128       116     0.0      48       0.0     0.0
Alum              7.2    112       116     0.0      48       0.0     0.0
Rapid Mix         7.2    112       116     0.0      48       0.0     0.0
Flocculation      7.2    112       116     0.0      48       0.0     0.0
Settling Basin    7.2    112       116     0.0      48       0.0    62.2
Lime              7.9     78       177    94.6      48       0.0    62.2
Rapid Mix         7.9     78       177    94.6      48       0.0    62.2
Softening Basin   7.9     78       130    47.3      48       0.0   109.5
Settling Basin    7.9     78        92     9.5      48       0.0   147.3
Carbon Dioxide    7.5     88        92     0.0      48       0.0   147.3
Chlorine          7.3     85        92     0.0      48       0.0   147.3
Ammonia           7.4     86        92     0.0      48       0.0   147.3
Filtration        7.4     86        92     0.0      48       0.0   147.3
Clearwell         7.4     86        92     0.0      48       0.0   147.3
WTP Effluent      7.4     86        92     0.0      48       0.0   147.3
Settling Basin    7.4     86        92     0.0      48       0.0   147.3
Dist. Sample      7.4     86        92     0.0      48       0.0   147.3
End of System     7.4     86        92     0.0      48       0.0   147.3
Notes:
 1) Floc* is CaCO3 precipitate plus super-saturated CaCO3.  The precipitate
    is removed by a Softening Basin while the super-saturated CaCO3 will
    pass through the basin.  Similar for Mg(OH)2 Floc*.
 2) Magnesium hardness (mg/L as CaCO3) and Floc* (mg/L as Mg(OH)2).
```

FIGURE A-5 USEPA WTP modeling software results screen

TABLE A-2 Actual Rossdale WTP plant 2 process data and model results

Date	Raw water quality					Chemicals			Alum Clarifier	Lime clarifier	ANN model predictions				USEPA model prediction
	temp	pH	total hardness	alkalinity	[1]ELS Raw Calcium Hardness	Alum dose	Lime dose	[2]Lime dose as $Ca(OH)_2$	pH	Total hardness	Alum clarifier pH	Alum dose	Lime clarifier total hardness	Lime dose	Lime clarifier total hardness
1-Jan-97	6	7.9	187	141	131.4	14	65	85.8	7.69	115.3	7.7	12.8	112.1	64.3	118
2-Jan-97	6	7.9	188	145	130.1	12	64	84.5	7.76	112.3	7.7	9.8	112.8	64.5	119
3-Jan-97	6	7.9	190	142	126.2	12	66	87.1	7.73	115.0	7.7	11.0	112.4	65.5	118
4-Jan-97	8.2	7.9	194	153	130.0	12	69	91.1	7.77	112.9	7.8	10.2	113.4	70.5	119
5-Jan-97	7	7.9	195	155	133.3	14	70	92.4	7.72	113.5	7.7	12.4	113.3	73.1	119
6-Jan-97	8	8	194	151	135.0	14	72	95.0	7.72	114.1	7.7	16.1	110.9	70.4	113
7-Jan-97	8	8	196	151	135.1	11	72	95.0	7.78	112.3	7.8	13.4	111.1	69.8	113
8-Jan-97	7	8	196	149	136.3	13	68	89.8	7.82	114.7	7.7	11.1	113.0	69.2	120
9-Jan-97	9	7.9	190	152	132.5	13	70	92.4	7.83	113.9	7.8	9.0	112.9	67.8	113
10-Jan-97	10	7.9	188	149	132.1	10	69	91.1	7.8	113.4	7.8	9.5	112.1	67.3	109
11-Jan-97	9.4	7.9	187	140	132.0	9	63	83.2	7.76	112.0	7.8	10.3	112.0	64.8	115
12-Jan-97	9.6	7.9	185	139	126.7	10	63	83.2	7.75	115.9	7.8	10.7	111.7	62.4	114
13-Jan-97	6.3	7.9	184	132	126.5	9	61	80.5	7.76	109.3	7.8	12.0	111.1	61.1	116
14-Jan-97	7.4	8	182	129	124.7	9	58	76.6	7.74	112.9	7.8	12.4	110.2	57.5	115
15-Jan-97	7	8	182	149	129.3	10	58	76.6	7.77	115.1	7.8	13.8	110.9	62.9	116
16-Jan-97	8	8	181	142	129.4	10	58	76.6	7.75	110.4	7.8	13.2	110.2	61.3	115
17-Jan-97	9	8	181	139	124.3	10	56	73.9	7.78	111.3	7.8	11.5	110.9	59.2	118
18-Jan-97	9	8	179	135	122.9	10	55	72.6	7.81	112.1	7.8	10.0	110.6	55.6	117
19-Jan-97	6	8	178	132	120.3	13	55	72.6	7.82	113.4	7.8	10.5	111.3	54.4	119
22-Jan-97	8.8	8	177	135	122.8	10	50	66.0	7.82	111.3	7.7	9.0	116.1	51.3	122
23-Jan-97	8	8	175	134	120.2	10	50	66.0	7.79	110.7	7.7	9.0	115.3	50.2	120
24-Jan-97	8	7.9	172	130	116.3	10	48	63.4	7.77	110.8	7.7	9.0	113.5	48.1	121
25-Jan-97	7	7.9	170	126	117.9	10	45	59.4	7.74	113.3	7.7	11.0	112.6	46.1	123
26-Jan-97	7	7.9	171	128	119.5	10	45	59.4	7.75	115.5	7.7	10.3	113.4	46.8	124
27-Jan-97	7	7.9	170	129	119.6	10	47	62.0	7.73	113.6	7.7	11.2	112.6	46.7	121
28-Jan-97	8	8	173	133	122.4	9	49	64.7	7.81	115.1	7.7	9.0	114.9	48.1	118
29-Jan-97	7.3	8	177	135	119.1	11	49	64.7	7.82	114.4	7.7	9.0	117.3	51.1	124
30-Jan-97	7	8	178	126	122.0	12	50	66.0	7.71	114.2	7.7	11.3	115.6	52.1	124
31-Jan-97	7.5	8	180	135	127.0	15	52	68.6	7.66	117.0	7.7	15.0	114.3	55.2	126
1-Feb-97	7.3	8	176	137	122.6	15	54	71.3	7.64	113.6	7.7	16.4	111.6	53.7	120
2-Feb-97	6.6	8	176	135	120.5	15	54	71.3	7.64	111.8	7.7	15.9	111.6	53.8	120
3-Feb-97	6	8	170	133	118.3	15	49	64.7	7.63	109.9	7.7	16.2	110.7	49.8	121
4-Feb-97	6	8	169	129	116.5	16	48	63.4	7.61	113.5	7.7	16.8	110.4	48.5	122
5-Feb-97	5	8	168	132	113.8	20	52	68.6	7.55	109.4	7.6	21.0	109.8	51.1	120
6-Feb-97	7	7.9	165	129	111.6	20	52	68.6	7.52	107.1	7.6	26.0	108.1	49.2	118
7-Feb-97	9.4	7.9	165	127	114.0	20	52	68.6	7.51	102.1	7.6	29.1	106.6	50.4	117
8-Feb-97	8	8	168	130	119.3	20	52	68.6	7.5	108.4	7.6	25.0	108.1	51.8	119
9-Feb-97	5.6	8	170	134	119.8	20	51	67.3	7.53	109.5	7.6	23.2	110.7	52.6	123
10-Feb-97	5.6	8	170	134	120.4	20	51	67.3	7.59	108.6	7.6	19.2	112.7	51.6	123
11-Feb-97	5.8	8	172	132	120.1	20	52	68.6	7.58	112.1	7.6	19.9	113.6	52.8	123
12-Feb-97	5	7.9	172	132	116.4	20	53	70.0	7.59	115.3	7.6	21.5	114.8	52.4	124
13-Feb-97	6	8	168	131	110.9	20	50	66.0	7.57	110.3	7.6	20.2	112.0	50.5	122
14-Feb-97	5.5	8	164	132	114.6	20	52	68.6	7.54	111.1	7.6	22.8	110.4	48.5	116
15-Feb-97	5.5	8	167	129	116.6	19	52	68.6	7.57	107.3	7.6	20.1	112.2	49.9	117
16-Feb-97	6	8	169	130	118.5	21	51	67.3	7.58	118.1	7.6	19.5	113.0	50.2	122
17-Feb-97	5.5	8	168	128	118.0	20	54	71.3	7.56	121.3	7.6	20.6	112.4	48.8	117
18-Feb-97	5.7	8	166	126	118.9	20	49	64.7	7.57	110.3	7.6	19.7	112.4	49.1	121
19-Feb-97	5.7	8	172	133	118.4	20	50	66.0	7.57	114.1	7.6	20.8	113.6	52.8	126
20-Feb-97	8.5	8	168	133	113.8	20	50	66.0	7.58	113.8	7.6	20.8	110.6	50.6	121
21-Feb-97	8	8	165	125	113.0	20	47	62.0	7.53	110.2	7.6	22.4	109.3	49.5	122
22-Feb-97	6	8	160	124	114.2	20	43	56.8	7.56	111.5	7.6	20.1	110.8	45.6	123
23-Feb-97	6	8	164	126	119.0	20	45	59.4	7.57	115.3	7.6	19.6	112.0	47.3	124
24-Feb-97	4	8	165	127	119.0	25	50	66.0	7.52	115.2	7.5	24.8	114.3	50.3	123
28-Feb-97	0.5	8	158	121	113.0	15	46	60.7	7.63	107.5	7.6	19.1	116.5	42.6	114
1-Mar-97	0.5	8	160	131	114.8	15	45	59.4	7.61	116.0	7.6	19.8	116.0	43.8	118
2-Mar-97	0.5	8	160	129	115.0	15	47	62.0	7.62	114.3	7.6	19.2	116.2	43.7	115
3-Mar-97	1	8	165	124	120.1	15	49	64.7	7.63	114.6	7.6	18.4	118.2	46.2	117
4-Mar-97	5	8	168	127	118.8	15	50	66.0	7.61	115.2	7.6	17.6	114.3	49.0	118
5-Mar-97	7	8	169	130	120.3	15	52	68.6	7.59	110.8	7.6	19.2	111.6	50.6	116
6-Mar-97	7.2	8	167	129	119.4	15	46	60.7	7.61	110.7	7.6	17.6	112.3	49.2	121
7-Mar-97	8.1	8	168	132	121.4	14	48	63.4	7.63	114.6	7.7	17.1	111.8	49.3	119
8-Mar-97	6.5	8	173	135	118.9	15	50	66.0	7.63	115.7	7.6	17.7	114.6	52.3	125
9-Mar-97	5.3	8	171	140	118.0	15	51	67.3	7.62	116.3	7.6	19.5	114.0	51.4	120
10-Mar-97	6.6	8	170	131	119.5	15	50	66.0	7.64	114.3	7.6	16.0	113.8	50.1	119
13-Mar-97	9	8	159	126	113.2	14	47	62.0	7.62	108.7	7.7	16.5	108.2	45.3	111
14-Mar-97	8.3	8	160	123	116.1	14	46	60.7	7.62	110.5	7.7	16.0	109.2	45.6	113
15-Mar-97	8.6	8	162	126	115.3	14	46	60.7	7.65	113.3	7.7	14.6	110.4	46.2	115

Table A-2 continued

Date	Raw water quality					Chemicals			Alum Clarifier	Lime clarifier	ANN model predictions				USEPA model prediction
	temp	pH	total hardness	alkalinity	[1]ELS Raw Calcium Hardness	Alum dose	Lime dose	[2]Lime dose as $Ca(OH)_2$	pH	Total hardness	Alum clarifier pH	Alum dose	Lime clarifier total hardness	Lime dose	Lime clarifier total hardness
16-Mar-97	8.4	8	163	119	115.3	14	45	59.4	7.67	112.9	7.7	12.5	111.5	46.5	118
17-Mar-97	10	8	162	122	115.3	15	47	62.0	7.7	112.6	7.7	11.2	110.4	46.4	115
18-Mar-97	9.6	8	161	121	110.4	17	48	63.4	7.66	108.5	7.6	14.1	110.5	48.9	114
22-Mar-97	7	8	154	117	111.1	28	48	63.4	7.42	105.9	7.5	32.5	106.8	47.3	117
23-Mar-97	6	8	151	110	107.8	26	46	60.7	7.43	110.1	7.5	31.9	107.2	44.2	115
24-Mar-97	6	8	148	115	105.3	25	42	55.4	7.49	107.8	7.5	25.7	107.4	42.1	117
25-Mar-97	0.7	8	149	124	107.8	23	40	52.8	7.5	110.1	7.6	28.1	113.6	42.2	120
26-Mar-97	0.5	8	150	118	108.0	22	38	50.2	7.51	115.1	7.5	27.9	114.3	42.0	123
27-Mar-97	0.5	8	152	117	106.5	25	41	54.1	7.52	116.4	7.5	27.3	115.2	43.3	123
28-Mar-97	0.5	8	152	118	109.3	41	49	64.7	7.36	113.2	7.3	43.0	114.0	47.9	127
29-Mar-97	0.5	8	154	131	110.0	67	60	79.2	7.23	115.2	7.2	60.8	113.4	57.1	137
30-Mar-97	0.5	8	147	127	105.9	83	63	83.2	7.03	114.6	7.1	91.8	111.7	61.6	140
31-Mar-97	0.5	8	137	120	97.7	94	63	83.2	6.94	112.8	7.0	103.1	111.4	60.1	139
1-Apr-97	1	7.9	125	109	86.6	138	58	76.6	6.88	111.8	6.8	127.1	111.3	60.8	173
2-Apr-97	1	7.9	123	107	87.7	117	50	66.0	6.78	113.7	6.8	131.3	111.6	57.0	163
3-Apr-97	1	8	127	108	90.1	120	70	92.4	6.71	115.3	6.8	119.3	114.1	66.1	143
4-Apr-97	3.6	8	132	113	94.1	118	70	92.4	6.71	115.5	6.8	119.7	113.8	70.9	145
5-Apr-97	7.6	8	137	114	99.1	106	69	91.1	6.82	111.8	6.8	110.6	111.2	70.2	140
6-Apr-97	4.1	8	141	125	102.7	91	68	89.8	6.92	112.6	6.9	89.9	110.5	68.5	133
7-Apr-97	1	8	152	121	110.0	75	66	87.1	7.05	112.9	7.0	73.3	114.5	65.0	134
8-Apr-97	1	8.1	156	131	110.0	75	75	99.0	7.02	114.3	7.1	78.7	113.1	69.6	124
9-Apr-97	1	8	153	132	109.0	79	70	92.4	7	109.9	7.1	87.4	111.5	70.3	133
10-Apr-97	1	8	156	127	109.1	70	65	85.8	7.04	113.3	7.1	79.5	112.9	66.8	135
11-Apr-97	1	8.1	160	129	110.2	56	62	81.8	7.13	110.1	7.2	64.4	112.9	64.7	129
12-Apr-97	1	8.1	162	135	115.2	54	56	73.9	7.21	112.9	7.2	59.0	112.4	63.0	137
13-Apr-97	1	8.1	162	136	112.8	54	58	76.6	7.25	116.6	7.3	55.5	112.5	60.8	134
14-Apr-97	1.2	8.1	146	135	102.6	72	55	72.6	7.17	111.0	7.1	63.7	111.1	58.4	138
15-Apr-97	1.4	8	136	117	97.0	92	57	75.2	6.96	113.8	6.9	90.4	111.5	58.5	144
16-Apr-97	1.3	8	130	110	87.9	107	59	77.9	6.9	110.8	6.8	97.4	113.0	60.6	149
17-Apr-97	1.4	8	120	102	90.5	114	57	75.2	6.75	113.1	6.7	112.6	113.9	58.0	147
18-Apr-97	1	8	116	102	84.0	118	58	76.6	6.71	113.3	6.8	121.4	113.1	56.8	146
10-May-97	13.4	8.3	166	133	115.6	60	66	87.1	7.23	106.6	7.3	71.6	108.9	67.4	128
11-May-97	14.5	8.3	172	139	118.5	61	64	84.5	7.24	111.6	7.3	67.7	112.0	68.1	137
12-May-97	14.8	8.4	173	141	118.3	56	63	83.2	7.27	112.6	7.4	63.2	113.4	65.8	134
13-May-97	14.8	8.4	171	141	116.5	56	65	85.8	7.32	111.0	7.4	58.0	111.1	64.9	129
14-May-97	16.2	8.4	169	136	119.0	58	65	85.8	7.28	110.6	7.3	59.7	111.9	65.8	129
15-May-97	17.8	8.3	173	137	118.0	60	70	92.4	7.3	113.8	7.3	58.0	112.7	68.5	129
16-May-97	19	8.4	174	138	121.3	53	68	89.8	7.31	111.6	7.3	56.3	112.6	67.4	125
17-May-97	17	8.4	178	137	123.0	47	68	89.8	7.39	110.9	7.4	50.5	112.6	68.1	124
18-May-97	14	8.4	177	139	122.1	52	66	87.1	7.33	112.2	7.4	57.3	113.7	70.8	131
19-May-97	12	8.4	176	137	122.6	48	64	84.5	7.39	116.0	7.4	54.6	112.8	66.1	129
20-May-97	11	8.4	178	142	123.3	41	63	83.2	7.52	113.7	7.5	45.4	112.8	61.2	126
23-May-97	10	8.3	173	136	118.0	50	65	85.8	7.42	114.4	7.4	50.2	111.9	62.2	128
24-May-97	9.9	8.3	168	140	114.7	70	67	88.4	7.25	115.1	7.2	67.3	111.8	68.0	138
25-May-97	10.6	8.3	165	141	111.9	98	74	97.7	7.02	115.5	7.0	92.3	115.1	77.9	150
26-May-97	11	8.3	163	140	111.4	101	75	99.0	6.94	113.9	7.0	101.2	114.8	79.7	149
27-May-97	12	8.2	162	135	111.2	107	83	109.6	6.92	117.4	6.9	110.2	115.1	79.1	144
28-May-97	13	8.3	159	128	111.7	88	78	103.0	7.01	110.0	7.0	91.0	109.8	74.2	130
29-May-97	14	8.3	161	133	114.8	82	68	89.8	7.13	112.8	7.1	78.7	112.1	69.1	139
30-May-97	16.6	8.3	162	130	112.1	78	64	84.5	7.13	111.5	7.1	79.3	114.8	68.1	142
31-May-97	18.2	8.3	157	128	115.0	79	55	72.6	7.06	119.5	7.1	89.4	123.1	60.6	149
1-Jun-97	18.7	8.3	157	127	112.4	79	52	68.6	7.08	125.7	7.1	87.2	126.5	55.2	153
2-Jun-97	18.8	8.3	161	131	111.1	74	51	67.3	7.14	128.3	7.2	80.2	127.8	53.8	153
3-Jun-97	19.1	8.3	161	133	109.1	74	53	70.0	7.22	126.8	7.2	70.8	126.3	53.1	151
4-Jun-97	17.2	8.3	160	129	111.3	72	46	60.7	7.21	131.7	7.2	69.5	130.5	49.7	157
5-Jun-97	16.7	8.3	164	129	116.5	67	53	70.0	7.25	127.2	7.2	64.4	123.3	53.4	148
6-Jun-97	17	8.4	173	134	118.5	68	57	75.2	7.24	126.7	7.2	65.1	127.7	60.3	152
7-Jun-97	18	8.4	180	140	120.4	61	59	77.9	7.32	126.4	7.3	58.5	126.9	61.5	150
8-Jun-97	19	8.4	178	140	122.1	51	56	73.9	7.41	126.5	7.4	50.6	125.2	56.0	143
9-Jun-97	19.6	8.5	176	141	124.4	46	49	64.7	7.48	126.8	7.4	44.3	129.2	52.0	144
10-Jun-97	20.23	8.5	173	136	122.7	46	52	68.6	7.41	125.8	7.4	47.7	125.2	50.6	138
11-Jun-97	20.5	8.4	172	134	118.0	48	51	67.3	7.4	126.4	7.4	48.8	126.1	49.6	141
12-Jun-97	20.6	8.5	175	129	118.8	40	50	66.0	7.39	122.6	7.5	47.1	125.0	51.3	138
13-Jun-97	20	8.5	174	132	117.7	34	46	60.7	7.54	125.9	7.6	37.7	126.5	45.8	137
14-Jun-97	20	8.4	168	130	117.9	39	47	62.0	7.53	123.1	7.5	38.1	124.5	45.2	135
15-Jun-97	20	8.3	168	129	115.5	42	47	62.0	7.46	122.9	7.5	43.0	122.7	47.2	138

Table A-2 continued

Date	Raw water quality					Chemicals			Alum Clarifier	Lime clarifier	ANN model predictions				USEPA model prediction
	temp	pH	total hardness	alkalinity	[1]ELS Raw Calcium Hardness	Alum dose	Lime dose	[2]Lime dose as $Ca(OH)_2$	pH	Total hardness	Alum clarifier pH	Alum dose	Lime clarifier total hardness	Lime dose	Lime clarifier total hardness
16-Jun-97	21	8.3	163	128	112.0	68	52	68.6	7.3	125.5	7.2	58.6	126.7	50.3	149
17-Jun-97	22	8.4	167	138	112.8	79	60	79.2	7.14	132.6	7.1	76.9	129.8	56.7	150
18-Jun-97	20.4	8.4	158	123	115.8	80	63	83.2	7.07	122.5	7.0	77.8	121.7	57.9	140
19-Jun-97	19.7	8.4	167	134	113.1	71	58	76.6	7.15	127.1	7.2	74.4	125.9	57.6	147
21-Jun-97	16.7	8.4	160	122	111.2	53	55	72.6	7.33	120.3	7.3	55.0	119.0	53.9	129
22-Jun-97	15.8	8.4	147	121	113.7	56	48	63.4	7.32	125.2	7.3	56.9	122.8	47.5	128
24-Jun-97	15.4	8.1	158	130	105.7	164	77	101.6	6.84	126.8	6.8	159.6	126.0	79.2	197
25-Jun-97	17	8.2	151	133	102.0	182	79	104.3	6.58	133.1	6.7	177.3	133.2	80.8	200
26-Jun-97	18	8.2	156	135	103.4	175	84	110.9	6.57	134.0	6.6	175.6	131.2	81.9	193
27-Jun-97	17.8	8.2	153	133	103.4	162	85	112.2	6.62	123.3	6.7	170.8	125.2	82.9	179
28-Jun-97	17.4	8.3	155	129	103.0	140	74	97.7	6.75	126.6	6.7	131.8	131.6	78.0	175
29-Jun-97	17	8.3	157	130	107.8	121	72	95.0	6.82	125.5	6.8	121.4	126.3	74.6	163
30-Jun-97	16.5	8.3	165	130	112.8	101	65	85.8	6.9	130.1	7.0	109.8	128.2	69.9	163
1-Jul-97	17	8.4	171	137	112.8	86	68	89.8	7.06	131.4	7.1	85.8	123.3	65.7	151
3-Jul-97	18	8.5	169	135	114.9	72	61	80.5	7.18	124.6	7.2	69.5	125.4	61.1	145
4-Jul-97	19	8.4	168	126	110.8	65	59	77.9	7.17	126.1	7.2	70.6	122.0	57.1	142
5-Jul-97	20	8.5	167	132	115.6	45	50	66.0	7.37	121.9	7.4	50.9	123.0	51.0	134
6-Jul-97	21	8.5	164	131	114.4	42	47	62.0	7.43	124.5	7.4	45.9	123.8	47.0	132
7-Jul-97	21.1	8.5	164	133	114.1	44	46	60.7	7.45	124.7	7.4	44.9	125.8	47.0	135
8-Jul-97	21.8	8.4	167	139	114.3	46	48	63.4	7.43	129.9	7.4	49.4	126.6	46.2	138
9-Jul-97	21.4	8.4	168	137	116.8	38	47	62.0	7.51	124.4	7.5	42.3	124.8	46.2	133
10-Jul-97	20	8.4	168	136	117.4	41	45	59.4	7.49	126.6	7.5	43.1	127.3	46.0	139
11-Jul-97	19	8.5	164	131	120.1	44	48	63.4	7.42	124.8	7.4	46.7	123.8	46.7	133
12-Jul-97	18	8.4	161	132	111.2	44	45	59.4	7.41	124.5	7.5	48.2	124.3	45.1	135
13-Jul-97	17	8.4	156	129	107.7	53	46	60.7	7.38	124.4	7.4	50.8	125.0	46.0	137
14-Jul-97	18	8.3	158	133	113.9	103.4	60.6	80.0	7.07	129.6	7.0	92.2	128.9	60.9	163
15-Jul-97	20	8.4	156	133	115.3	118.8	68.4	90.3	6.92	130.0	6.9	107.6	131.1	67.0	162
16-Jul-97	20.7	8.4	154	140	114.2	111	69.3	91.5	6.9	127.7	6.9	113.0	125.8	66.0	153
17-Jul-97	20.6	8.4	152	136	110.4	83	58.7	77.5	7.01	120.9	7.1	97.0	122.8	58.6	141
18-Jul-97	20	8.4	153	124	107.2	59.4	41.9	55.3	7.17	125.0	7.3	70.2	128.0	46.9	144
19-Jul-97	20.2	8.4	159	128	108.7	64.2	42.4	56.0	7.24	134.8	7.2	63.1	132.3	44.3	153
20-Jul-97	21.8	8.4	154	129	108.9	59.9	45.6	60.2	7.22	131.5	7.3	65.3	128.0	41.4	140
21-Jul-97	22	8.3	157	126	110.1	73.7	47.5	62.7	7.14	129.5	7.2	78.7	130.5	47.7	153
22-Jul-97	23	8.5	161	134	114.7	64.3	45.5	60.1	7.25	137.5	7.2	60.3	134.2	43.3	149
23-Jul-97	22.6	8.44	163	138	117.1	63.6	45.5	60.1	7.29	137.3	7.3	58.6	135.7	43.6	151
24-Jul-97	21.7	8.5	161	133	113.3	58.3	43.4	57.3	7.31	133.9	7.3	53.8	134.1	41.7	147
25-Jul-97	20.7	8.5	161	131	114.5	46.8	41.1	54.3	7.39	131.9	7.4	47.0	131.4	39.0	140
26-Jul-97	19.3	8.48	160	128	112.0	43.9	37.6	49.6	7.41	130.0	7.4	45.6	131.7	38.7	142
27-Jul-97	18.9	8.4	160	132	118.6	42.2	38	50.2	7.38	132.6	7.5	49.3	131.1	37.9	140
28-Jul-97	19.9	8.5	160	130	111.8	37.9	35.5	46.9	7.45	133.9	7.5	42.7	131.9	35.6	139
29-Jul-97	21.4	8.5	163	131	114.1	33.1	35.2	46.5	7.58	130.7	7.6	34.5	131.6	36.4	138
30-Jul-97	22	8.4	165	134	117.4	33.9	32.8	43.3	7.6	132.1	7.6	34.5	134.6	36.8	144
31-Jul-97	22	8.5	162	136	115.4	43.5	35.7	47.1	7.39	137.0	7.5	47.9	135.0	37.4	144
1-Aug-97	22.9	8.5	165	138	114.8	39.7	36.5	48.2	7.46	137.5	7.5	43.3	134.8	37.4	143
2-Aug-97	23.1	8.5	163	136	114.2	38.5	37.2	49.1	7.5	133.1	7.5	40.1	133.6	36.9	139
3-Aug-97	23	8.5	164	133	117.0	34.3	36.4	48.0	7.55	133.1	7.6	36.4	132.4	36.1	138
4-Aug-97	23.5	8.5	164	132	116.7	34.4	35.2	46.5	7.57	131.6	7.5	35.0	133.0	36.3	139
5-Aug-97	24.1	8.5	164	130	118.2	33.1	35.9	47.4	7.57	131.3	7.6	34.5	132.1	35.9	138
6-Aug-97	25.2	8.44	164	128	116.4	32.7	34.4	45.4	7.53	134.8	7.6	37.0	133.6	34.1	140
7-Aug-97	24.9	8.5	164	132	116.4	33.2	32.8	43.3	7.53	131.9	7.5	37.1	135.5	35.0	141
8-Aug-97	22.7	8.42	159	132	112.1	37.7	31.5	41.6	7.56	131.2	7.5	36.1	135.8	34.3	143
9-Aug-97	20	8.5	155	122	109.9	34.6	28.6	37.8	7.53	133.1	7.5	36.3	133.1	32.1	140

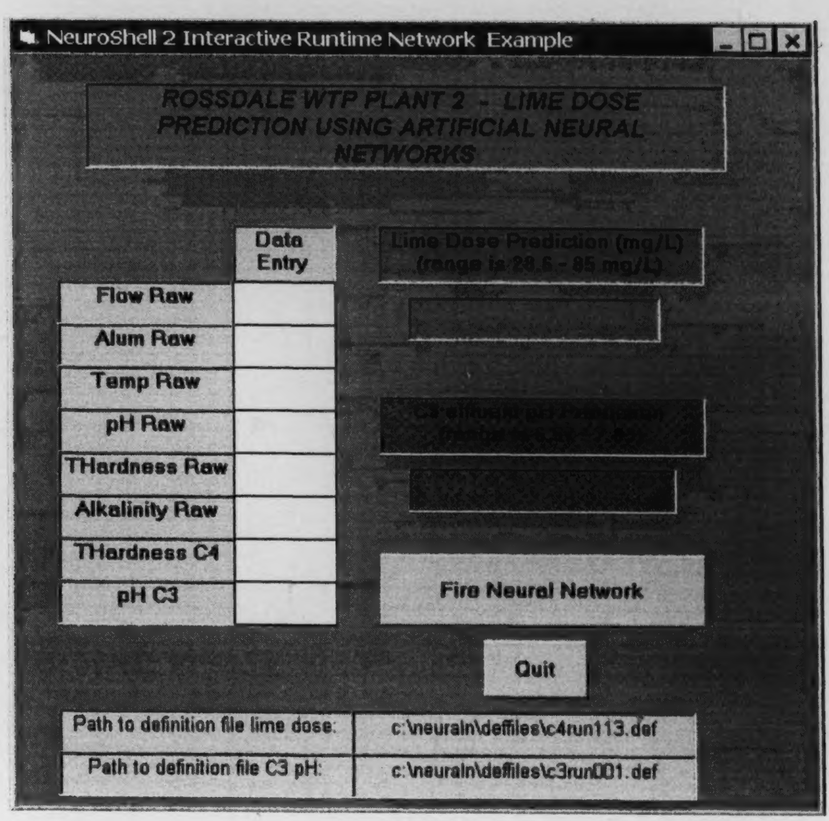
[1] The raw water calcium hardness data is required for the USEPA model and was retrieved from the E.L. Smith plant because it is not measured at Rossdale.

[2] Since the USEPA WTP model requires lime dose as Calcium Hydroxide and the plant measures lime as Calcium Oxide, the following equation was used to make the conversion:

$$CaO + H_2O = Ca(OH)_2$$

Calcium hydroxide dose = Calcium Oxide dose *1.32

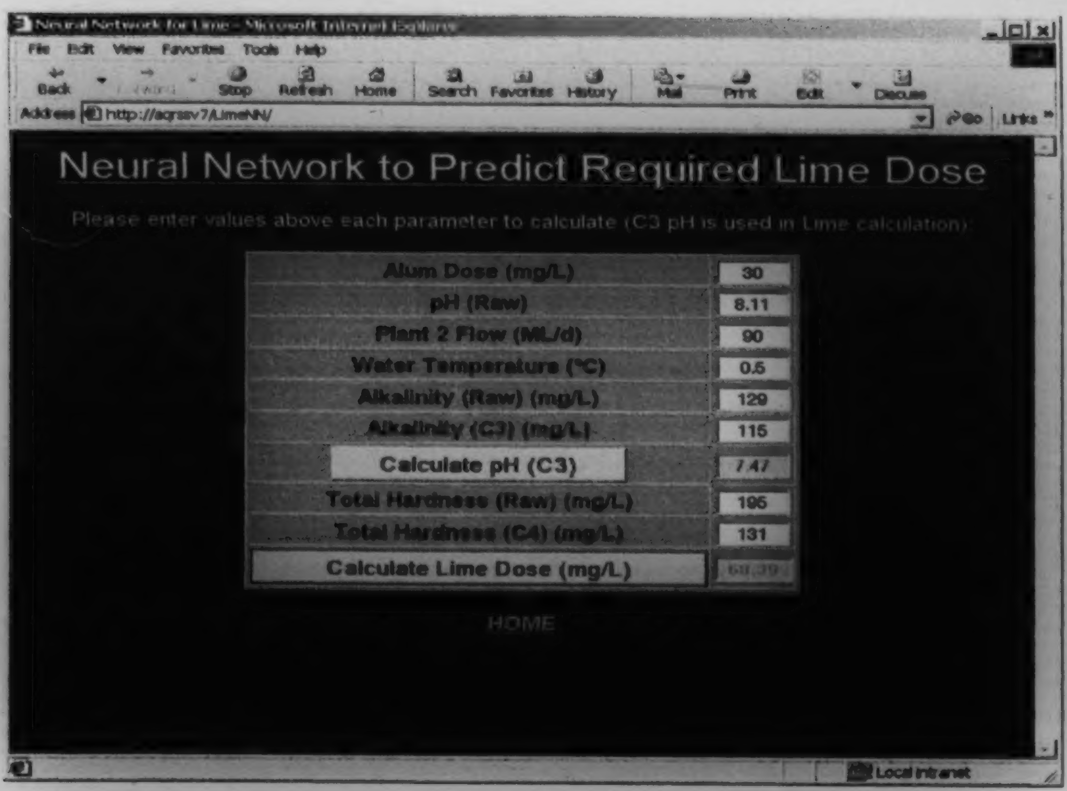
APPENDIX B Integration of Artificial Neural Networks with Real-time Process Control Systems


NeuroShell 2 Interactive Runtime Network Example
ROSSDALE WTP PLANT 2 - LIME DOSE PREDICTION USING ARTIFICIAL NEURAL NETWORKS
Data Entry
Flow Raw
Alum Raw
Temp Raw
pH Raw
THardness Raw
Alkalinity Raw
THardness C4
pH C3
Lime Dose Prediction (mg/L) (range is 28.6 - 85 mg/L)
C3 effluent pH Prediction (range is [illegible])
Fire Neural Network
Quit

Path to definition file lime dose: c:\neuraln\deffiles\c4run113.def

Path to definition file C3 pH: c:\neuraln\deffiles\c3run001.def

FIGURE B-1 A Visual Basic off-line user interface for ANN


Neural Network for Lime - Microsoft Internet Explorer
File Edit View Favorites Tools Help
Back
Forward
Stop
Refresh
Home
Search
Favorites
History
Mail
Print
Edit
Discuss
Address
http://aqrsv7/LimeNN/
Go
Links
Local intranet

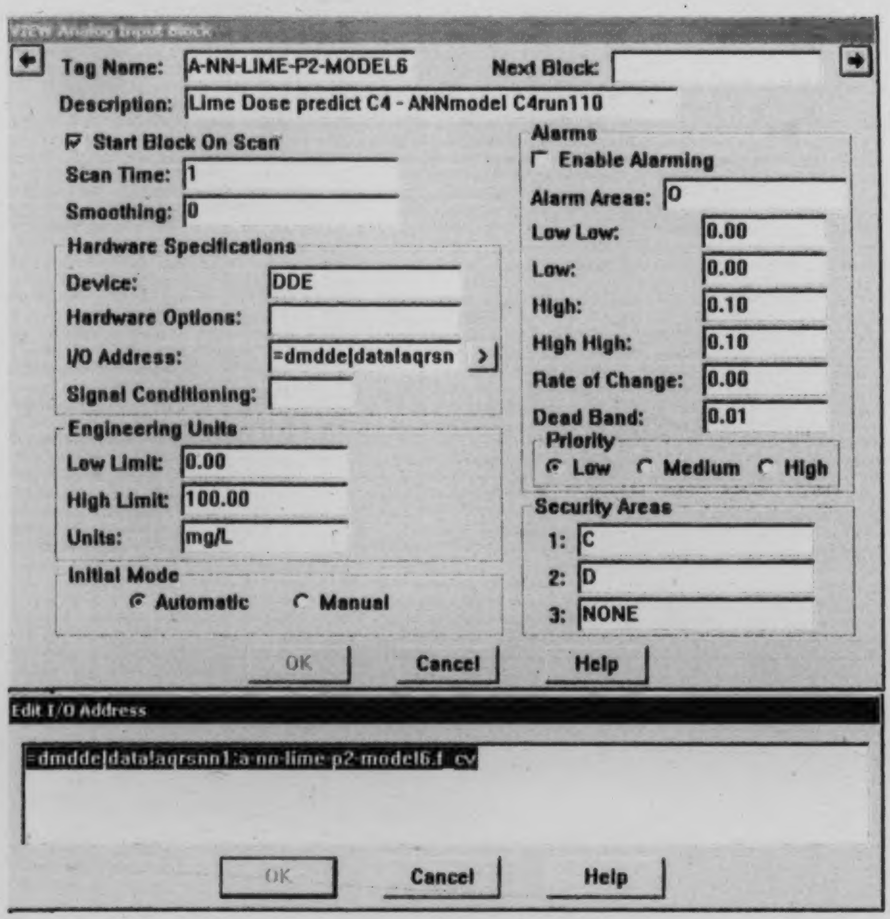
Neural Network to Predict Required Lime Dose

Please enter values above each parameter to calculate (C3 pH is used in Lime calculation)

Alum Dose (mg/L)	30
pH (Raw)	8.11
Plant 2 Flow (ML/d)	90
Water Temperature (°C)	0.5
Alkalinity (Raw) (mg/L)	129
Alkalinity (C3) (mg/L)	115
Calculate pH (C3)	7.47
Total Hardness (Raw) (mg/L)	196
Total Hardness (C4) (mg/L)	131
Calculate Lime Dose (mg/L)	68.39

HOME

FIGURE B-2 A web-based off-line user interface for ANN


VIEW Analog Input Block
Hardware Specifications
Engineering Units
Initial Mode
Alarms
Priority
Security Areas
OK
Cancel
Help
Edit I/O Address
OK
Cancel
Help

Tag Name: A-NN-LIME-P2-MODEL6
Next Block:
Description: Lime Dose predict C4 - ANNmodel C4run110

☑ Start Block On Scan
Scan Time: 1
Smoothing: 0

Device: DDE
Hardware Options:
I/O Address: =dmdde|data!aqrsn
Signal Conditioning:

Low Limit: 0.00
High Limit: 100.00
Units: mg/L

● Automatic ○ Manual

☐ Enable Alarming
Alarm Areas: 0
Low Low: 0.00
Low: 0.00
High: 0.10
High High: 0.10
Rate of Change: 0.00
Dead Band: 0.01

● Low ○ Medium ○ High

1: C
2: D
3: NONE

=dmdde|data!aqrsnn1:a-nn-lime-p2-model6.f_cv

FIGURE B-3 Analog input read-back configuration on SCADA database

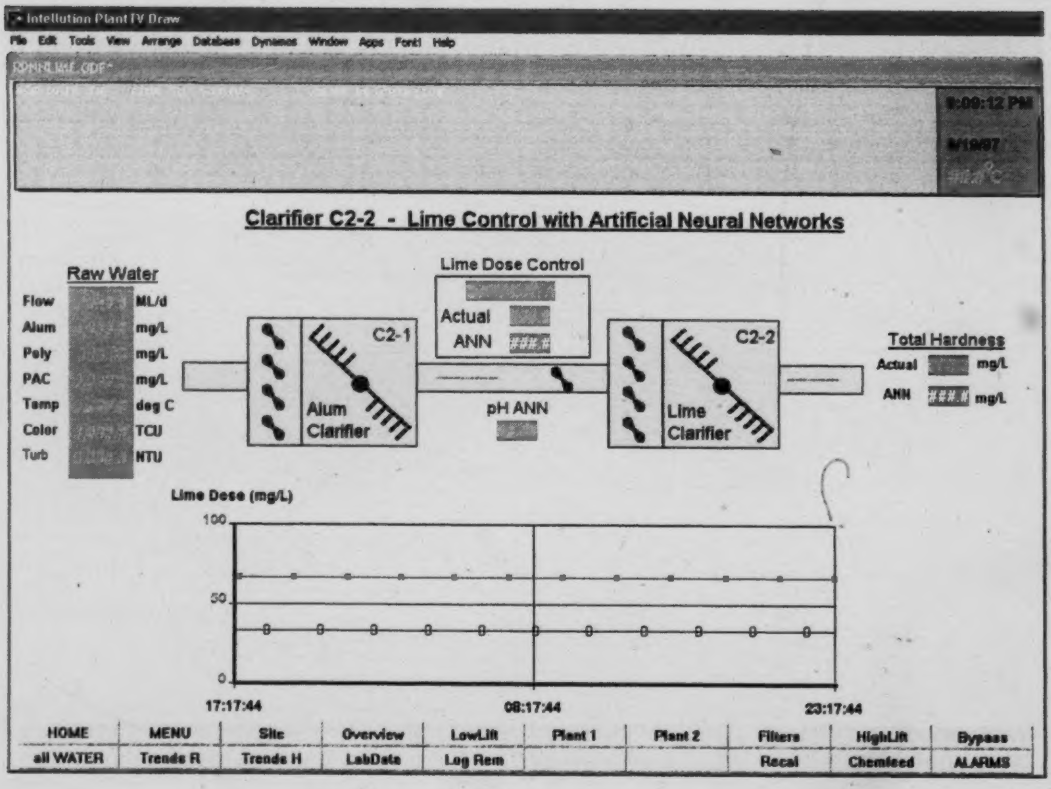

Intellution PlantTV Draw
File Edit Tools View Arrange Database Dynamos Window Apps Fonts Help
9:09:12 PM
8/19/97
Clarifier C2-2 - Lime Control with Artificial Neural Networks
Raw Water
Flow ML/d
Alum mg/L
Poly mg/L
PAC mg/L
Temp deg C
Color TCU
Turb NTU
Lime Dose Control
Actual
ANN ###.#
C2-1
Alum Clarifier
pH ANN
C2-2
Lime Clarifier
Total Hardness
Actual mg/L
ANN ###.# mg/L
Lime Dose (mg/L)
100
50
0
17:17:44
08:17:44
23:17:44
HOME
MENU
Site
Overview
LowLift
Plant 1
Plant 2
Filters
HighLift
Bypass
all WATER
Trends R
Trends H
LabData
Log Rem
Recal
Chemfeed
ALARMS

FIGURE B-4 Real-time ANN interface on plant SCADA HMI

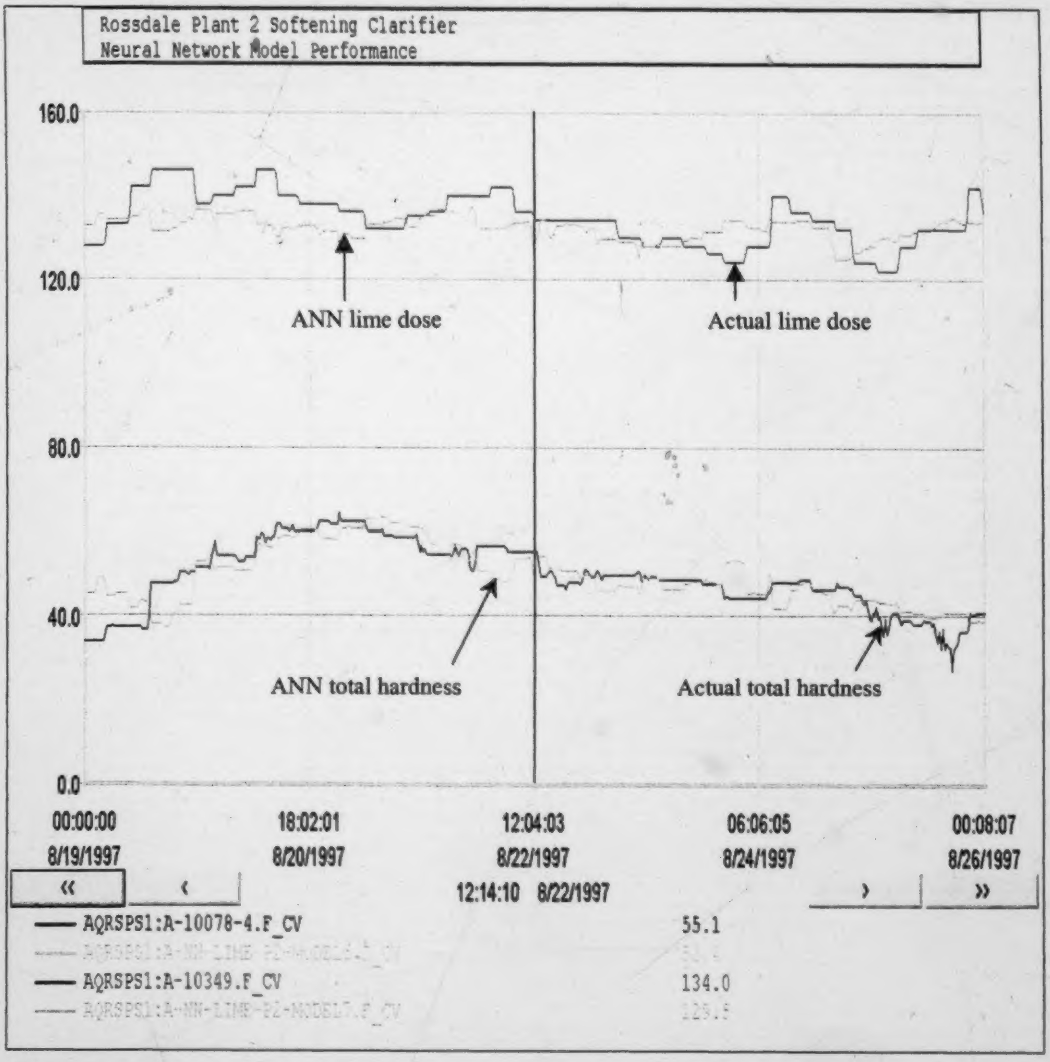


FIGURE B-5 Lime dose and total hardness actual and ANN predicted values from the SCADA historian

APPENDIX C Remote Monitoring and Operation of Isolated Small Water Facilities in Cold Regions

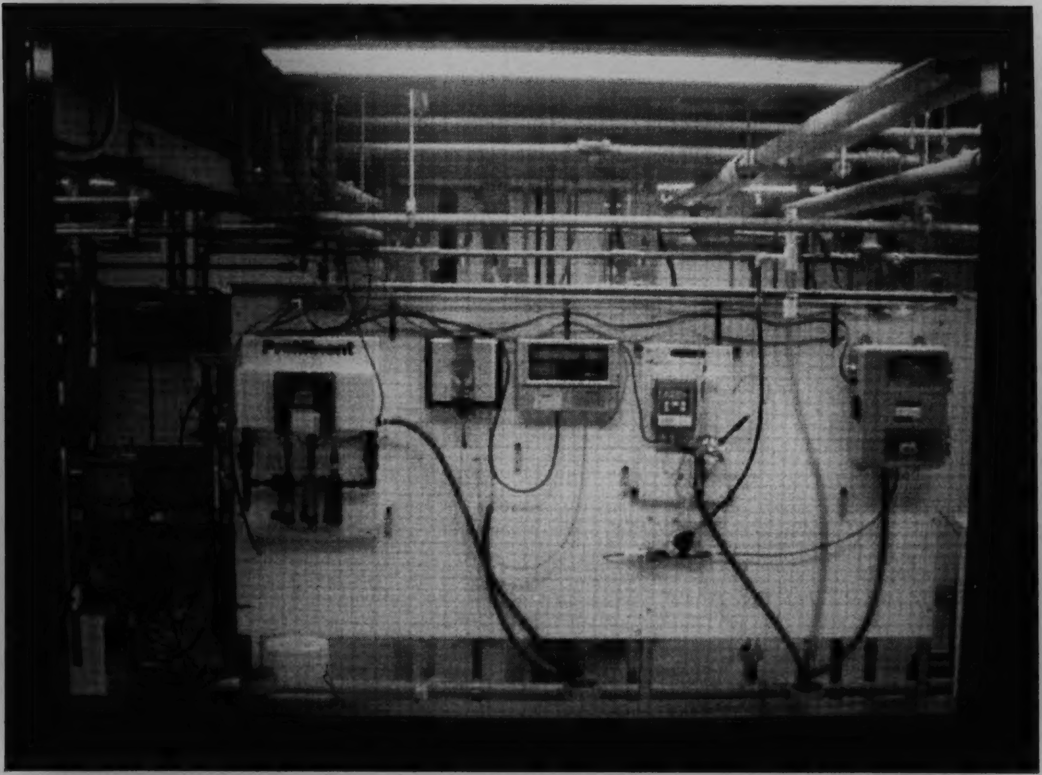


FIGURE C-1 Chlorine analyzer pilot test layout at the Rossdale Water Treatment Plant

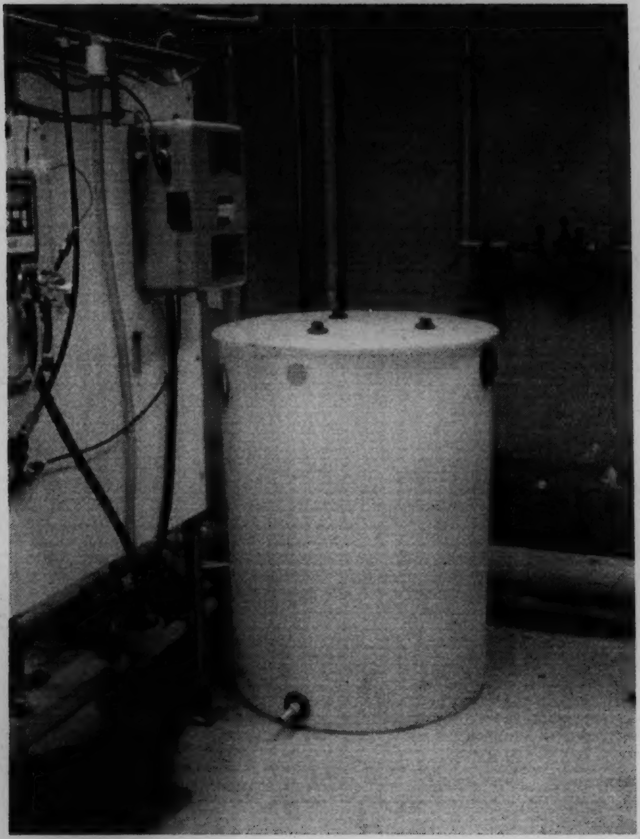


FIGURE C-2 Chlorine analyzer pilot test – chlorine sample recirculation tank

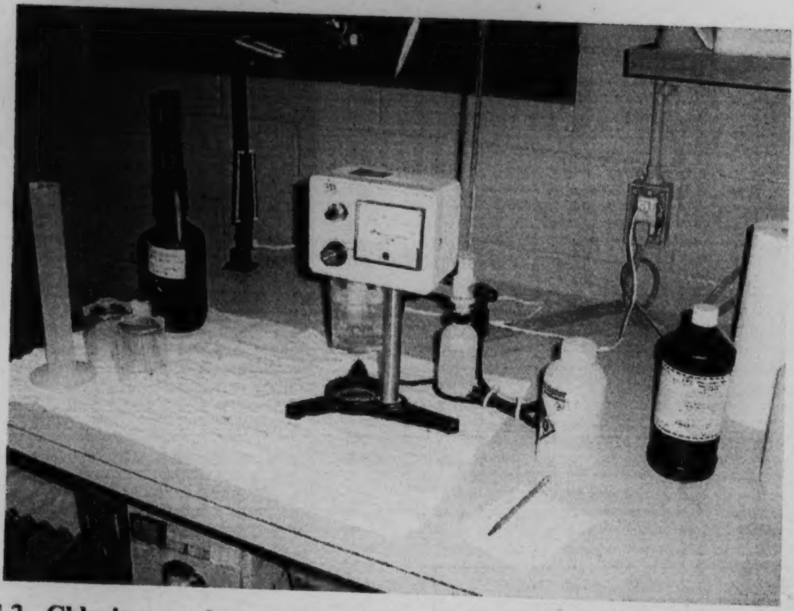


FIGURE C-3 Chlorine analyzer pilot test – bench chlorine residual measurement equipment

TABLE C-1 Raw data from the on-line chlorine analyzer pilot test (all values are in mg/L free chlorine) (after Penny, 2001)

Original Measurement Data						
Reading	Bench Average	ProMinent D1C	W & T Depolox 3+	Swan FAM Trides	Hach CL17	Endress & Hauser
1	2.23		2.25	2.21	2.28	
2	2.09		2.02	1.97	2.10	
3	2.24		2.11	2.14	2.25	
4	2.30		2.16	2.13	2.30	
5	2.33		2.24	2.13	2.36	
6	2.18	2.17	2.10	1.87	2.22	
7	2.10	2.17	2.08	2.12	2.10	
8	2.12	2.17	2.00	2.01	2.16	
9	2.11	2.12	1.98	2.02	2.15	
10	2.34	2.12	2.16	2.35	2.43	
11	2.34	2.12	2.15	2.36	2.42	
12	2.18	2.12	1.99	2.24	2.21	
13	1.92	2.12	1.79	2.01	1.97	
14	2.37	1.92	2.37	2.38	2.42	
15	2.39	1.92	2.31	2.38	2.43	
16	2.35	1.92	2.33	2.39	2.39	
17	2.35	1.92	2.28	2.39	2.40	
18	2.26	1.92	2.19	2.22	2.33	
19	2.21	1.92	2.15	2.20	2.32	
20	2.21	1.92	2.12	2.20	2.28	
21	2.24	1.92	2.13	2.28	2.29	
22	2.28	1.92	2.14	2.58	2.31	
23	2.25	1.92	2.47	2.46	2.34	
24	2.38	1.92	2.52	3.71	2.47	
25	1.70	1.90	1.85	1.82	1.77	
26	1.50	1.77	1.74	1.77	1.59	
27	1.12	1.18	1.13	1.41	1.17	
28	0.97	1.00	0.97	1.24	1.01	1.07
29	0.63	0.65	0.60	0.87	0.66	0.68
30	0.50	0.53	0.47	0.73	0.52	0.56
31	0.98	0.83	0.49	0.51	1.02	0.83
32	0.54	0.51	0.44	0.52	0.56	0.52
33	1.27	1.32	1.92	1.50	1.30	1.29
34	1.16	1.21	1.14	1.16	1.21	1.18
35	0.96	0.99	0.89	0.97	0.99	0.96
36	0.23	0.23	0.11	0.21	0.25	0.25
37	1.03	1.19	1.15	1.22	1.07	1.23
38	0.94	0.88	0.85	0.85	0.97	0.90
39	0.68	0.58	0.51	0.53	0.72	0.62
40	0.60	0.49	0.41	0.45	0.62	0.54
41	0.38	0.30	0.23	0.27	0.39	0.34
42	0.34	0.28	0.18	0.23	0.34	0.31
43	0.66	0.80	1.09	0.62	0.69	0.85
44	0.57	0.61	0.52	0.51	0.58	0.51
45	0.81	0.77	0.43	0.43	0.86	0.68
46	1.20	1.96	1.68	2.04	1.26	1.26
47	1.15	1.80	1.52	1.88	1.18	1.18
48	0.96	1.48	1.30	1.30	1.02	1.02
49	1.40	1.60	1.30	1.36	1.46	1.50
50	0.70	0.53	0.42	0.27	0.75	0.62
51	0.32	0.23	0.19	0.07	0.36	0.29
52	0.64	0.71	0.59	0.49	0.67	0.70
53	0.24	0.17	0.15	0.04	0.27	0.22
54	1.41	2.64	2.54	7.59	1.46	1.53
55	0.42	0.31	0.31	0.16	0.44	0.40
56	0.93	0.63	0.54	0.32	0.95	0.83
57	0.62	0.37	0.34	0.16	0.64	0.54
58	0.22	0.10	0.10	0.00	0.22	0.19
59	0.47	0.24	0.20	0.08	0.49	0.43
60	0.60	0.60	0.65	0.50	0.64	0.75
61	0.61	0.50	0.32	0.13	0.65	0.58
62	1.08	0.90	0.45	0.23	1.13	0.98
63	0.62	0.75	0.53	0.26	0.66	0.69
64	0.23	0.18	0.12	0.00	0.23	0.22
65	0.85			0.43	0.86	0.80
66	0.67			0.35	0.68	0.64
67	0.41			0.33	0.44	0.44
68	1.56	1.50	1.44	1.61	1.61	1.72
69	1.54	1.50	1.42	1.60	1.60	1.71
70	1.54	1.50	1.40	1.58	1.57	1.69
71	1.56	1.50	1.49	2.02	1.63	1.71
72	1.57	1.50	1.48	2.04	1.64	1.70

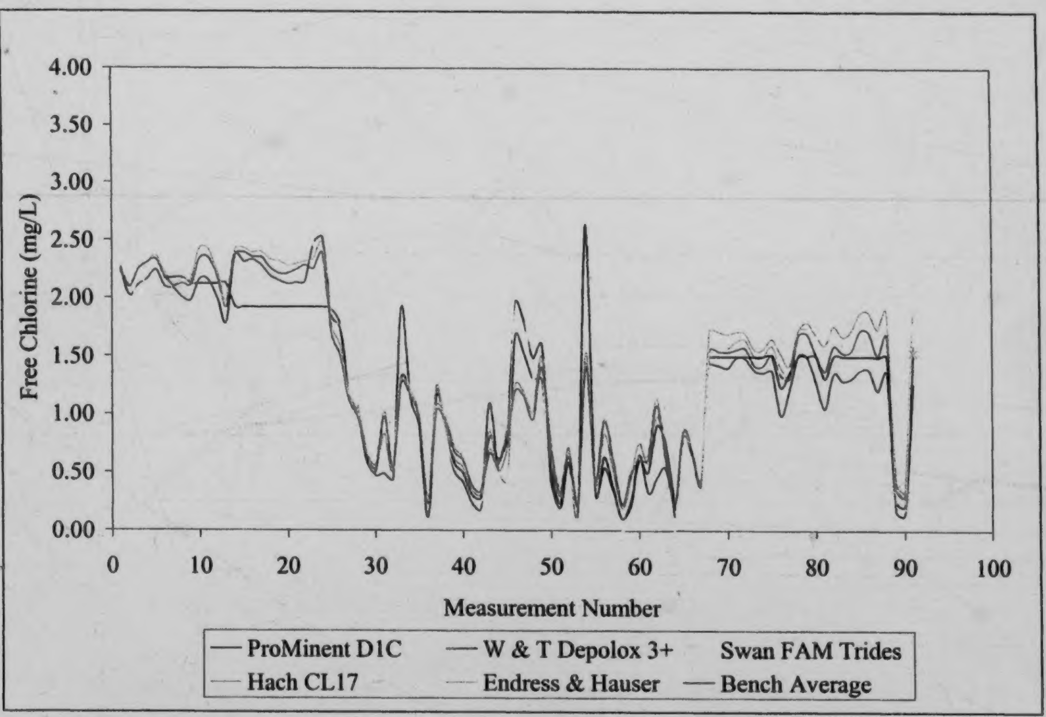
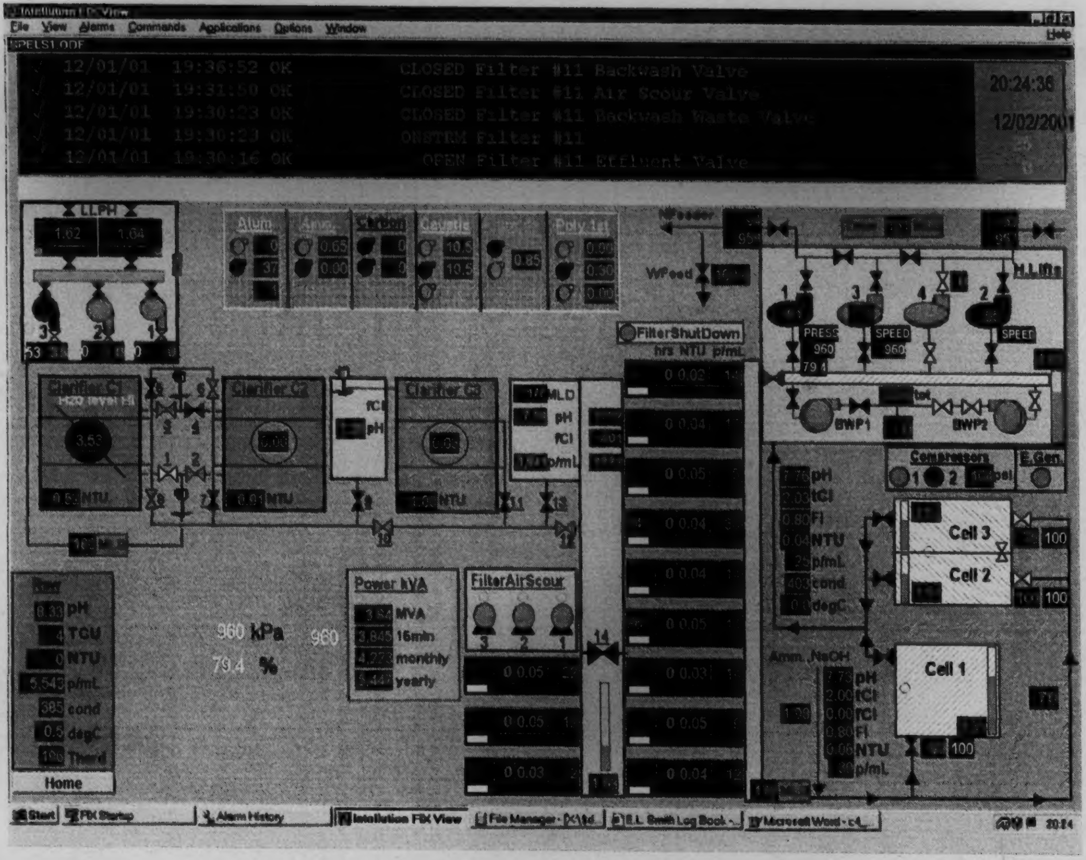


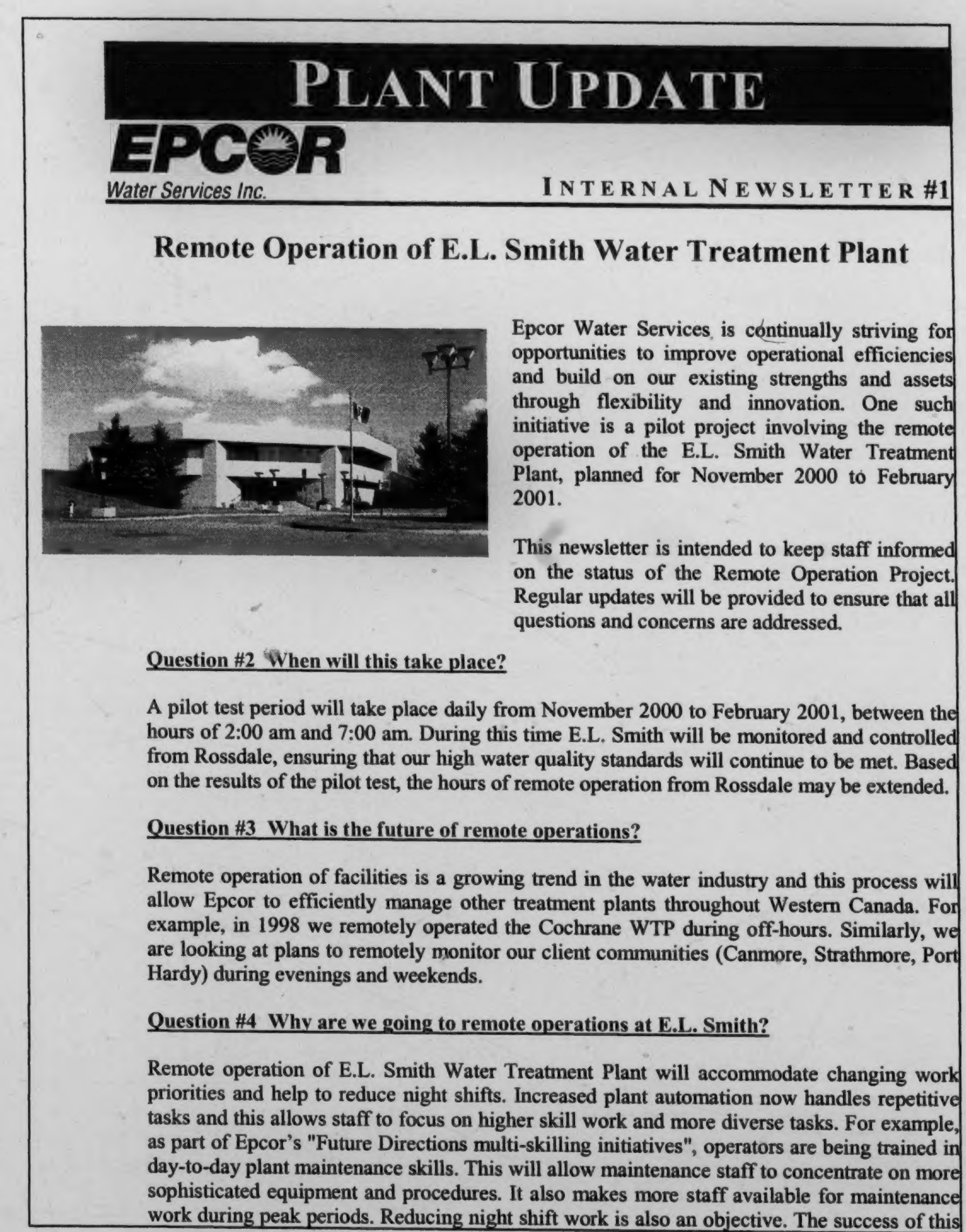
FIGURE C-4 Trend of raw data from the on-line chlorine analyzer pilot test

TABLE C-2 Cost analysis of various on-line chlorine analyzers

Analyzer	Capital Cost (including $2000 installation allowance)	Annual Operating Costs and Maintenance Time	1st year investment (assuming a staff wage of $30.00/hour)	2nd year investment	Annual Life Cycle Costs (no interest accounted for)
ProMinent	$8,500	$200 plus 30 min/week	$9,500	$1000	$1,850
W & T Depolox 3+	$6,800	$400 plus 45 min/week	$8,400	$1,600	$2,300
Swan FAM Trides	$12,500	13 hours/year	$12,900	$400	$1,650
HACH CL17	$6,300	$760 plus 1 hour/month	$7,400	$1,100	$1,750
Endress & Hauser	$6,900	1 hour/month	$7,300	$360	$1,050

APPENDIX D Automation and Unattended Operation of the E.L. Smith Water Treatment Plant





PLANT UPDATE

EPCOR
Water Services Inc.

INTERNAL NEWSLETTER #1

Remote Operation of E.L. Smith Water Treatment Plant

Epcor Water Services is continually striving for opportunities to improve operational efficiencies and build on our existing strengths and assets through flexibility and innovation. One such initiative is a pilot project involving the remote operation of the E.L. Smith Water Treatment Plant, planned for November 2000 to February 2001.

This newsletter is intended to keep staff informed on the status of the Remote Operation Project. Regular updates will be provided to ensure that all questions and concerns are addressed.

Question #2 When will this take place?

A pilot test period will take place daily from November 2000 to February 2001, between the hours of 2:00 am and 7:00 am. During this time E.L. Smith will be monitored and controlled from Rossdale, ensuring that our high water quality standards will continue to be met. Based on the results of the pilot test, the hours of remote operation from Rossdale may be extended.

Question #3 What is the future of remote operations?

Remote operation of facilities is a growing trend in the water industry and this process will allow Epcor to efficiently manage other treatment plants throughout Western Canada. For example, in 1998 we remotely operated the Cochrane WTP during off-hours. Similarly, we are looking at plans to remotely monitor our client communities (Canmore, Strathmore, Port Hardy) during evenings and weekends.

Question #4 Why are we going to remote operations at E.L. Smith?

Remote operation of E.L. Smith Water Treatment Plant will accommodate changing work priorities and help to reduce night shifts. Increased plant automation now handles repetitive tasks and this allows staff to focus on higher skill work and more diverse tasks. For example, as part of Epcor's "Future Directions multi-skilling initiatives", operators are being trained in day-to-day plant maintenance skills. This will allow maintenance staff to concentrate on more sophisticated equipment and procedures. It also makes more staff available for maintenance work during peak periods. Reducing night shift work is also an objective. The success of this

FIGURE D-2a E.L. Smith Remote Operations Newsletter #1 Page 1 of 2

Question #6 What has been done so far?

1. An Implementation committee (staff from Operations, Maintenance, Engineering, Lab, and Process Services) is reviewing and recommending changes related to technical issues, as well as staffing and training. Shift change issues are being handled at the Charge Operators meetings and through the Implementation committee.
2. The systems (chemical, electrical, on-line analyzers, pumping, security and controls) have been reviewed and work has begun on any recommended changes. For example, the filter controls are currently being automated.
3. "Policy on Automated/Unattended Operation of Surface Water Treatment Plants" (10 States Standards; Recommended Standards for Water Works 1997 edition) is being used as a guideline for this project.

Question #7 Will this initiative affect the current operator shift schedule?

Yes. Since the Plant will be unmanned for 4 – 6 hours, a change in shift schedule is required. A new shift schedule is being proposed with the addition of a 12 hour shift between 2:00 pm. and 2:00 am. However, creative ideas for a new shift schedule are welcome. Please contact the Implementation Committee.

Question #8 How will this initiative benefit staff?

This program will benefit staff in two ways:

- Night shift work will be reduced.
- There will be increased opportunity to train and expand technical skills in other areas.

Question #9 Will this initiative result in job losses?

No. There are no expectations or plans to reduce the existing staff levels as a result of this project. In fact, multi-skill trained staff will have increased opportunities as our business continues to grow and evolve.

Contacts

Riyaz Shariff
Rudy Welz
Woytec Stachowski
Denis Lavoie
Christian Madsen
Dave Wong (Lab)
Norm Spitzer
Andy Chichak
Rick Corscadden
Rob Towstego
Tina Mendes
Scott Evjen
Dan Sliwkanich
Dennis Lavallee
Howard Preston
Clayton Ernst

FIGURE D-2b E.L. Smith Remote Operations Newsletter #1 Page 2 of 2